MBA Consultancy Project

AI Agent–Enabled Case Scoring and Assignment: Strategic Impact on Customer Lifecycle Management in Regulated Financial Services

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This portfolio is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the University of York.

Declaration of Originality: I declare that this work is my own and has not been submitted elsewhere.

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Abstract

This consultancy project investigates the role of artificial intelligence (AI) in customer service case management within the financial services sector, focusing on a stock brokerage firm with CRM integration.

The study explores how AI-driven case scoring and automated assignment can improve operational efficiency, service quality, and compliance in regulated environments. A mixed-methods design combined an online survey of industry practitioners (n=150), 12 semi-structured interviews with CRM managers, IT specialists, and compliance officers, and secondary performance data.

Findings indicate that AI-enabled case routing enhances service-level agreement (SLA) compliance and reduces response times, while also surfacing concerns about data privacy, transparency, and employee trust. Both survey respondents and interviewees acknowledged AI's benefits but stressed the importance of explainable algorithms, governance, and effective change management to ensure adoption.

The report provides actionable recommendations: a phased AI deployment supported by human oversight, robust governance frameworks to address ethical and regulatory issues, and structured change management to maximize benefits while mitigating risks.

Keywords: Customer Relationship Management (CRM); Artificial Intelligence; Case Assignment; Service Operations; Financial Compliance; Mixed-Methods Research.

Content

Summary (Portfolio Overview)

This MBA consultancy portfolio presents an integrated set of five tasks that collectively demonstrate the research, application, and reflection involved in addressing a real-world business challenge using academic and practical tools.

The project investigates how artificial intelligence (AI) can improve case scoring and assignment within customer service operations in the financial services industry. Using a mixed-methods approach, the consultancy explored both performance metrics and human perceptions, generating insight into the efficiency, trust, and compliance dimensions of AI implementation.

The findings show that AI can significantly improve operational KPIs such as SLA compliance and customer satisfaction while also raising challenges related to transparency and governance. The report offers actionable recommendations for responsible adoption, including phased deployment, algorithm oversight, and organizational readiness planning.

This portfolio reflects the culmination of learning from the MBA program and applies module insights in strategy, operations, digital transformation, and leadership. It also demonstrates the ability to conduct independent research, apply critical thinking, and produce practical, evidence-based recommendations for complex business issues.

Poster (Key Take-Away Message)

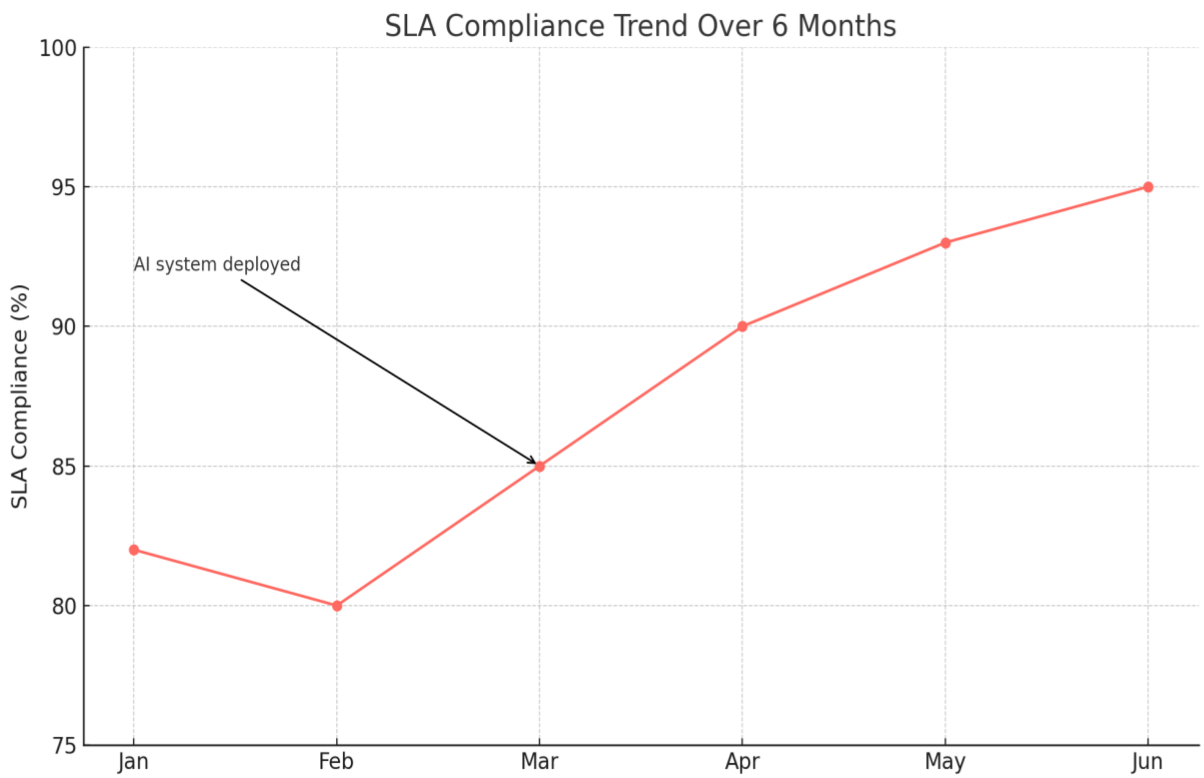

Figure 1: SLA Compliance Before and After AI Deployment (Jan–Jun)

Take-Away Message

From Chaos to Compliance: How AI Transformed Customer Service

AI did not replace human agents — it empowered them. By automating case prioritisation and routing, the system freed staff to focus on complex, high-value issues where human judgment matters most.

Within just three months, SLA compliance increased from **82% to 95%**, first-response times dropped by more than half, and customer satisfaction rose.

The result: faster resolutions, balanced workloads, and service quality that exceeded regulatory and client expectations.

Introduction and Research Context

Customer service operations in the financial services sector face growing pressure to deliver faster responses, consistent service, and strict regulatory compliance (Accenture, 2021; McKinsey & Company, 2022). This consultancy project investigates the strategic and operational implications of implementing artificial intelligence (AI)–enabled support within Customer Relationship Management (CRM) systems. The focus is the adoption of automated case scoring and assignment in a German stock brokerage's customer support process.

The firm currently manages thousands of client inquiries relating to trades, accounts, and compliance. Cases are logged into the CRM system and routed manually by human agents. This manual triage is often slow and inconsistent: urgent issues such as failed high-value trades may not be prioritised quickly enough, while routine queries are sometimes misrouted (Salesforce, 2023; Gartner, 2023). Leadership has identified AI as a potential solution for classifying and prioritising cases in real time, assigning them directly to the most appropriate agents (IBM, 2020)

However, the potential introduction of AI raises several uncertainties. Efficiency improvements are expected, yet concerns remain over algorithmic bias, transparency, GDPR compliance, and employee acceptance. Adoption in highly regulated industries has been cautious, and there is limited academic research on AI deployment within CRM-based case management (Accenture, 2021; McKinsey & Company, 2022).

Recent studies also emphasize the importance of explain ability and governance in AI-enabled service operations (Dwivedi et al., 2021; Jussila et al., 2022). Methodologically, the research design is guided by established approaches to business research (Saunders et al., 2023). This project therefore addresses a knowledge gap by assessing both the benefits and the risks of AI in a high-stakes, compliance-sensitive context.

- Research Aim and Objectives

The primary aim is to critically evaluate how AI-driven case scoring and routing affect customer service performance and risk management across the customer lifecycle. The key objectives are:

To measure AI's impact on operational outcomes such as response times, SLA compliance, and customer satisfaction (see Appendix C).

To explore stakeholder perceptions of AI adoption among service agents, IT staff, and compliance officers (see Appendix D).

To identify technical, ethical, and regulatory challenges, and to outline success factors for sustainable AI integration.

The ultimate goal is to develop practical recommendations for phased and responsible AI implementation within the brokerage.

- Research Questions

RQ1: To what extent can AI case prioritization and assignment improve resolution speed, SLA compliance, and overall customer experience in CRM-enabled financial services?

RQ2: What legal, ethical, and compliance risks arise when deploying AI in regulated service environments, and how can these be mitigated?

RQ3: How do stakeholders — including CRM staff, compliance personnel, and senior managers — perceive the strategic and operational implications of integrating AI into customer support?

These questions balance operational performance with compliance and human factors. Answering them requires an interdisciplinary approach, combining insights from information systems (AI in operations), organizational behavior (technology acceptance), and regulatory studies. This ensures the analysis remains both academically grounded and practically relevant for financial services organizations.

Literature Review

This literature review examines the strategic and operational impact of integrating artificial intelligence (AI) agents into customer relationship management (CRM) systems, with a focus on case scoring and assignment automation in regulated financial services. As service-level expectations intensify, organizations must reconcile efficiency demands with fairness, compliance, and employee acceptance.

Drawing from economics, organizational behavior, decision science, and applied CRM studies, the review critically evaluates how AI agents influence operational efficiency, stakeholder trust, and regulatory alignment.

To structure this discussion, a conceptual framework is adopted that synthesizes four interrelated domains where AI-enabled CRM agents create value and face challenges: (1) operational efficiency, (2) strategic value, (3) ethical and regulatory requirements, and (4) organizational readiness.

Figure 2 illustrates how these domains interact within financial-services case management. This framework guides the review and underpins the design of the empirical study, including survey development and coding of interview data (see Appendix E)

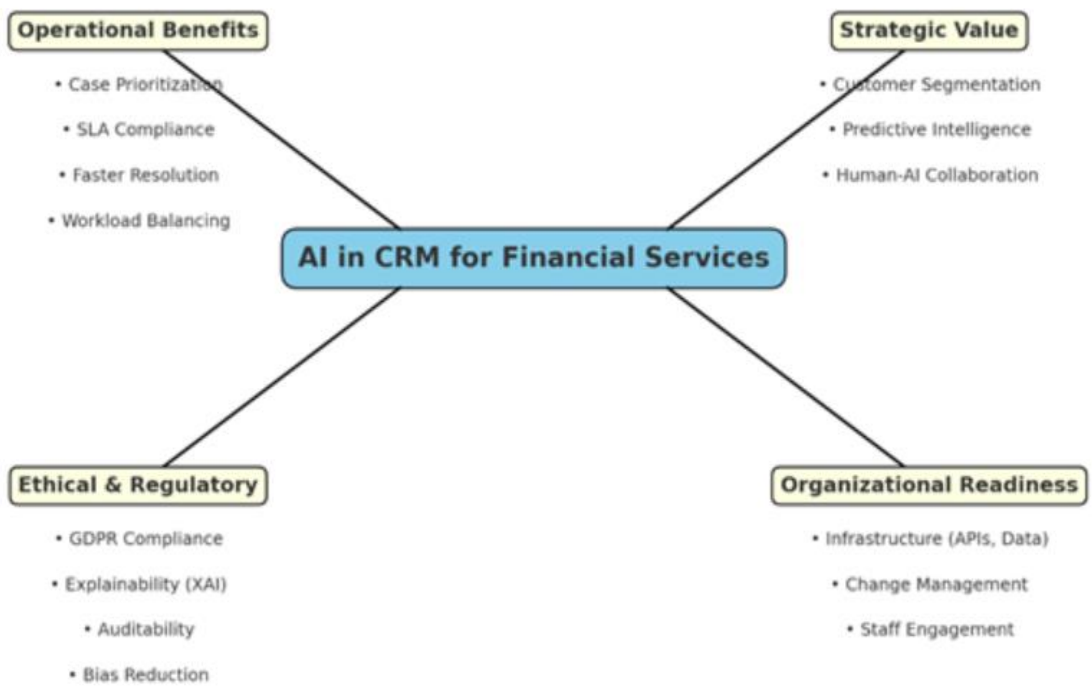

Figure 2: Conceptual framework of AI in CRM for financial services

- AI CRM Agents in Financial Services

AI has moved from experimental to embedded in modern CRM systems. Platforms such as Salesforce Einstein, Agentforce, and Microsoft Dynamics 365 AI apply historical interaction data to classify, prioritise, and route cases (Salesforce, 2023; Microsoft, 2022). In financial services — an industry marked by regulatory caution — competitive pressures and rising digital expectations have accelerated adoption (Accenture, 2021).

Trust in AI CRM agents depends not only on their technical competence but also on their transparency (Glikson and Woolley, 2020). These requirements are critical in finance, where opaque decisions risk breaching compliance or undermining customer trust. Sinclair (2005) situates current developments within the sector's long reliance on algorithmic decision-making, such as credit scoring, which foreshadow the predictive capabilities of today's AI-enabled systems.

AI in CRM therefore cannot be assessed purely as technology. Adoption raises questions across multiple dimensions: daily operational performance, longer-term strategic value, ethical and regulatory compliance, and organisational readiness for change.

While adoption has accelerated, scholars note that financial firms often approach AI CRM cautiously compared with less regulated sectors. Deloitte (2022) reports that many banks treat AI pilots as “regulatory sandboxes,” limiting deployment to non-critical workflows before scaling into compliance-heavy processes. This cautious approach contrasts with retail or telecommunications, where AI chatbots and automated case handling have been fully integrated into front-line operations (Accenture, 2021).

The literature also highlights a dual dynamic of competitive pressure and institutional conservatism. On one hand, digital-first entrants such as Revolut and N26 showcase the speed and agility possible with AI-driven CRM. On the other, established institutions prioritise reliability and reputational protection, delaying rollout until robust governance is in place. This tension echoes Rogers’ (2003) diffusion of innovations theory: innovators deploy quickly, while laggards wait for proven safety.

Theories of trust in automation add further depth. Lee and See (2004) argue that trust is calibrated not by technical accuracy alone but by system predictability, reliability, and transparency. Applied to CRM, this means staff are more likely to adopt AI when it consistently explains why a case is prioritised or routed. Without this, even accurate systems risk underuse due to perceived opacity.

Empirical research remains limited but growing. A recent Gartner (2023) survey found that 65% of financial services executives identified AI-enabled CRM as “strategic priority,” yet fewer than 30% had achieved enterprise-wide deployment. This implementation gap underscores that adoption is not a purely technological question but one of governance, integration, and cultural readiness.

- Operational Impacts: Efficiency, SLA Compliance, and Case Lifecycle

AI agents are widely associated with efficiency gains: reducing handling time, streamlining triage, and supporting service-level agreement (SLA) compliance. Wong and Lye (1990) show how value systems shape performance metrics, which resonates with how AI models prioritise cases by urgency, sentiment, or historical patterns.

McKinsey & Company (2022) report that firms using AI for service routing achieved resolution times up to 30% faster. Gartner (2023) and IBM (2020) highlight additional benefits in queue management and workload balancing.

In regulated environments, these gains extend beyond efficiency to compliance protection, since SLA breaches often carry regulatory implications. Xu (2001) demonstrates how data-driven contrarian strategies uncover hidden patterns, relevant to AI's potential for surfacing anomalies in unstructured case data.

Yet benefits cannot be assumed. Routing accuracy, system reliability, and continuous bias monitoring are essential. SLA gains may also be undermined if staff distrust AI outputs or cannot explain their logic to clients or regulators.

Operational research has long associated automation with efficiency, but CRM-specific studies add nuance. Parasuraman et al.'s (1988) SERVQUAL model identifies responsiveness as a central dimension of perceived service quality, and AI-enabled routing directly targets this dimension. By prioritising urgent cases and balancing workloads, AI not only improves SLA metrics but also contributes to customer satisfaction outcomes such as Net Promoter Score (NPS).

However, efficiency gains are not uniform. Susskind and Susskind (2015) note that automation benefits are often front-loaded, with diminishing returns over time as easy efficiency wins are exhausted. Applied to CRM, this suggests that SLA compliance may rise sharply after deployment but plateau unless systems are continuously updated. IBM (2020) stresses the need for "active learning loops" to ensure models adapt to new case types.

Another complexity is that AI routing interacts with human decision-making. Xu's (2001) findings on contrarian data strategies highlight the risk of over-reliance: AI may uncover anomalies, but staff must still contextualise them. Automation bias (Mosier & Skitka, 1996) occurs when humans over-trust AI outputs even when flawed, while under-reliance occurs when staff ignore accurate recommendations. Both behaviours can undermine SLA outcomes.

Finally, scholars note that efficiency metrics often fail to capture hidden costs. For example, faster routing may increase case throughput but also intensify employee workload, leading to digital fatigue or burnout (Tarafdar et al., 2015). Thus, while operational outcomes are generally positive, they must be balanced with human sustainability considerations.

- Strategic Value and Organisational Readiness

Beyond immediate efficiency, AI CRM agents create strategic value by embedding predictive intelligence and enabling dynamic resource allocation across the customer lifecycle. Tirole (1982; 1985) provides theoretical underpinnings for investing in predictive infrastructure under uncertainty. Davenport et al. (2020) argue that AI augments rather than replaces human decision-making, aligning with case assignment workflows where human oversight remains vital.

However, strategic value is conditional on organizational readiness. This includes technical capacity (data pipelines, retraining mechanisms, integration via APIs) and human alignment (employee acceptance, interdepartmental collaboration, and change management). Woodford (1986) notes that equilibrium in constrained systems is fragile — an apt metaphor for AI adoption in compliance-heavy settings. Tobin's (1958) liquidity preference theory, though economic in origin, illustrates the need to balance responsiveness with control.

Empirical studies show readiness depends less on algorithms themselves than on leadership support, communication, and workforce engagement (Accenture, 2021). Without inclusive change management, AI risks being resisted rather than embedded.

Strategic adoption of AI CRM must be seen as part of digital transformation agendas.

Westerman et al. (2014) argue that digital leaders excel not only by adopting technologies but by integrating them into business models and culture. In this sense, AI case assignment is not just a back-office tool but a strategic lever that can influence customer retention, compliance positioning, and even market reputation.

Organisational readiness is multidimensional. Henderson and Venkatraman's (1993) strategic alignment model emphasises that technology initiatives succeed when aligned with business strategy, organisational infrastructure, and human resources. In practice, this means AI CRM must be integrated with customer strategy (e.g., loyalty programs), IT systems (e.g., APIs, databases), and HR processes (e.g., training and role redefinition).

Failure to achieve alignment is a recurring problem. Studies of failed AI pilots in banking reveal that even technically sound models falter when frontline staff bypass them due to lack of trust (Accenture, 2021). Similarly, leadership inertia can derail adoption if executives hesitate to endorse AI systems publicly. Thus, the literature converges on a central insight: AI CRM generates strategic value only when treated as an organisational change initiative rather than a technical plug-in.

- ## Ethical and Regulatory Considerations

AI adoption in financial services is inseparable from compliance and ethics. The General Data Protection Regulation (GDPR) requires automated decision-making to be explainable and auditable. The forthcoming EU AI Act classifies financial applications such as credit scoring and triage as high risk, mandating human oversight (BaFin, 2022).
Binns et al. (2018) highlight tensions between accuracy and fairness, while Doshi-Velez and Kim (2017) stress that interpretability is essential for trust and accountability. Treynor's (1965) critique of performance evaluation frameworks applies to fairness in AI scoring, while Van Norden and Schaller (1999) warn that behavioural non-linearity may create unintended algorithmic bias.

Industry practice increasingly incorporates governance mechanisms such as AI ethics boards, fairness audits, and transparency dashboards. Evidence suggests that when AI systems provide clear rationales (e.g., "high priority due to sentiment analysis and client tier"), user trust increases (Glikson and Woolley, 2020). Without such safeguards, firms risk compliance failures and reputational damage.

The ethical dimension extends beyond regulatory compliance to encompass fairness, accountability, and societal trust. Mittelstadt et al. (2016) propose six key areas of ethical concern: privacy, accountability, transparency, bias, autonomy, and societal impact. In the CRM context, each of these is highly salient. For example, using customer sentiment data may inadvertently discriminate against clients whose communication style differs across cultures, raising fairness concerns.

Moreover, the EU AI Act's "high-risk" classification implies that financial organisations will need to implement ongoing human-in-the-loop oversight, not just during pilot stages but throughout the AI system lifecycle. This contrasts with less regulated industries, where full automation is possible. In practice, firms are likely to adopt hybrid models where AI triages but humans retain authority for final assignment in sensitive cases.

Ethical debates also extend to workforce impacts. Frey and Osborne (2017) argue that automation threatens mid-level service jobs, though empirical evidence shows augmentation is more common than replacement. Still, perceptions of job displacement can undermine morale and adoption, making transparent communication critical. Thus, ethics in AI CRM must be understood holistically: as a compliance obligation, an employee relations issue, and a foundation of customer trust.

- Gaps in the Literature

Despite progress, several critical gaps remain in the context of regulated financial services:

Sectoral focus: Much research examines marketing or conversational AI, but little empirical work addresses CRM case scoring and assignment in financial institutions.

Human–AI interaction: Few studies investigate how frontline staff interpret, contest, or override AI recommendations, even though regulators emphasise human oversight.

Model governance: West (1987) called for rigorous model validation, yet little evidence exists on how financial firms implement continuous retraining and exception handling. Most assume static models, overlooking CRM's dynamic data flows.

Behavioural dimensions: While Tversky and Kahneman (1974) show how biases shape decisions, research rarely explores automation bias, confirmation bias, or under-reliance in CRM settings.

Socio-technical impacts: Human factors such as digital fatigue, fairness perceptions, and emotional responses remain underexplored despite their influence on trust and compliance.

Integrative frameworks: Few studies combine operational, strategic, regulatory, and organisational dimensions into one model, even though these interact in practice.

This project addresses these gaps directly. By combining surveys, semi-structured interviews, and operational data analysis within a brokerage setting, it contributes original insights into how AI-enabled case scoring and assignment affect efficiency, compliance, and trust, and develops an applied framework for responsible adoption.

The persistence of these gaps reflects broader academic silos. Information systems research often emphasises technical architectures but underplays regulatory nuance. Organisational behaviour research foregrounds employee acceptance but neglects algorithmic design. Regulatory studies focus on compliance but rarely engage with lived organisational practices. Very few studies cross these boundaries to develop integrated frameworks.

Future research opportunities include longitudinal studies tracking AI CRM adoption over time, comparative analyses across regulatory regimes (e.g., EU vs US vs Asia), and experimental studies examining how explanation design influences employee trust. There is also scope for interdisciplinary frameworks that combine socio-technical systems theory with compliance governance, creating models tailored to the realities of financial services.

By addressing these gaps empirically, this project contributes both academic insight and practical guidance, advancing understanding of AI CRM in one of the world's most complex and regulated industries.

To synthesise these insights, Table 1 provides a comparison of academic literature and industry perspectives on AI in CRM within financial services. It highlights areas of consensus, divergence, and the research gaps that this study seeks to address.

Theme	Academic Literature	Industry / Consultancy Reports
Operational Efficiency	Studies highlight AI's potential to reduce handling times, streamline triage, and improve SLA compliance, but warn of risks from automation bias and over-reliance (Parasuraman et al., 1988; Xu, 2001; Mosier & Skitka, 1996).	McKinsey (2022) and Gartner (2023) report up to 30% faster resolution times and improved workload balance; IBM (2020) emphasises queue management benefits.
Strategic Value	Scholars emphasise organisational readiness, alignment with business strategy, and socio-technical equilibrium (Woodford, 1986; Henderson & Venkatraman, 1993; Davenport et al., 2020).	Accenture (2021) and Deloitte (2022) highlight digital transformation and ROI, framing AI as a competitive differentiator in customer lifecycle management.
Ethics & Compliance	Academic debates stress fairness, transparency, and human oversight; GDPR and EU AI Act mandate explainability and accountability (Doshi-Velez & Kim, 2017; Mittelstadt et al., 2016; BaFin, 2022).	Industry guidance promotes AI ethics boards, fairness audits, and transparency dashboards (Gartner, 2023; IBM, 2020).
Human Factors	Research emphasises trust calibration, workforce acceptance, and socio-technical challenges (Lee & See, 2004; Glikson & Woolley, 2020; Rogers, 2003).	Consultancy reports frame AI as augmentation rather than replacement, but note resistance from staff and the need for structured change management (Accenture, 2021; Deloitte, 2022).

Theme	Academic Literature	Industry / Consultancy Reports
Research Gaps	Lack of longitudinal and cross-sector studies; under-explored human–AI interaction and model governance (West, 1987; Tversky & Kahneman, 1974).	Industry insights often highlight best practice cases but provide limited empirical validation or independent evaluation (McKinsey, 2022; Salesforce, 2023).

Table 1. Comparison of Academic vs Industry Perspectives on AI in CRM for Financial Services

As shown in Table 1, academic work tends to emphasise theoretical constructs such as trust calibration, socio-technical alignment, and ethical governance, while industry reports are more pragmatic, focusing on efficiency gains, ROI, and digital transformation. This divergence illustrates why cross-sector research is essential: industry insights provide immediacy and practical case examples, whereas academic frameworks ensure critical depth and rigour. The present study builds on both traditions by combining empirical field data with conceptual analysis, thereby contributing to a more integrated understanding of AI-enabled CRM in regulated contexts.

Methodology

- Research Philosophy and Design

This study adopts a pragmatic paradigm, focusing on practical outcomes through mixed methods. Guided by Saunders et al. (2023), this approach combines quantitative and qualitative techniques to address the research questions synergistically. A pragmatic stance was chosen because it prioritises real-world problem solving over strict adherence to any single philosophical tradition, making it particularly appropriate for consultancy projects where actionable recommendations are the end goal (Easterby-Smith et al., 2021). Pragmatism also allows the researcher to flexibly draw on multiple perspectives, aligning methods with the research questions rather than forcing the study into a narrow epistemological frame.

The design follows an exploratory–explanatory sequence: survey data establishes patterns of AI's perceived impact, while interviews provide deeper explanations and context. Secondary organizational data further triangulates findings, strengthening validity and reliability. Applying both quantitative and qualitative techniques enables complementary insights: numerical data highlights trends and general perceptions, while qualitative accounts provide nuance, depth, and explanation. This combination not only enhances validity through triangulation but also ensures that both operational outcomes and human experiences are captured, reflecting the complexity of AI adoption in financial services.

- Data Collection Methods

Survey (Quantitative)

An online survey was distributed via Qualtrics and LinkedIn to capture practitioner perspectives on AI in customer support. After data cleaning, 152 valid responses were analyzed. The instrument (Appendix C) included Likert-scale items on perceived AI benefits (e.g., resolution time), multiple-choice questions on challenges (privacy, job impact), and open-ended comments. Participation was voluntary and anonymous, with roles spanning managers, IT staff, compliance officers, and senior management across financial services organizations.

Sampling technique and sample size: A non-probability purposive sampling strategy was used, targeting professionals in CRM, IT, and compliance roles**.** Purposive sampling was chosen because the study required insights from practitioners with direct experience of customer support processes and AI adoption, ensuring the data collected was relevant and informed by expertise (Saunders et al., 2023**).** Snowballing via LinkedIn shares extended reach**.**

Snowball sampling was particularly appropriate in this context because AI adoption in financial services is a specialised and relatively niche field; using professional networks allowed access to otherwise hard-to-reach participants and expanded the sample while maintaining relevance (Easterby-Smith et al., 2021). The achieved sample of 152 respondents provided breadth across functions while remaining within practical feasibility.

Interviews (Qualitative)

To deepen insights, 12 semi-structured interviews were conducted with survey participants and organizational stakeholders: five service agents/team leaders, four IT/CRM administrators, and three compliance officers. Each interview lasted ~40 minutes via Zoom, guided by a thematic protocol (Appendix D). Topics included personal AI experiences, workflow changes, perceived risks, and implementation recommendations.

Sampling technique and sample size: A purposive approach ensured coverage of frontline, technical, and compliance roles. From survey volunteers, 12 participants were selected to balance perspectives while remaining manageable for in-depth analysis.

Semi-structured interviews were chosen because they provide both structure and flexibility: key themes are consistently addressed across participants, while open-ended questions allow deeper exploration of individual perspectives (Braun & Clarke, 2006). This balance helps capture both comparability and richness, particularly valuable for studying perceptions of emerging technologies like AI.

Secondary Data (Documents and Metrics)

Anonymised performance reports from the brokerage — including SLA compliance, first-response time, and customer satisfaction — provided objective operational indicators. Internal documents (e.g., service handbook, IT policy) clarified workflows, while external industry reports benchmarked findings. Supporting visuals and anonymised extracts are provided in Appendix F.

Secondary data were used to complement primary data and strengthen triangulation. Organisational metrics offered objective performance evidence that could be compared with staff perceptions, reducing reliance on self-reported data alone. Using internal documents and external benchmarks also ensured contextual accuracy and allowed findings to be situated against industry standards (Denscombe, 2019). This combination enhanced the robustness and credibility of the analysis.

- Data Analysis

Quantitative survey data were analysed using descriptive statistics (frequencies, percentages) and cross-tabulations to explore subgroup differences (e.g., IT staff compared with service agents). Given the exploratory nature and sample size ($n \approx 150$), the analysis did not employ advanced inferential statistics. Instead, emphasis was placed on clear visualisation of trends.

Charts were created for key survey findings (see Results section), such as the distribution of responses on perceived efficiency gains (Figure 3) and reported challenges to AI adoption (Figure 4). These visuals clarified patterns in agreement, neutrality, and disagreement, making trends immediately interpretable (Field, 2018; Saunders et al., 2023).

Qualitative interview data were analysed through iterative coding. Following initial coding, four major themes were identified (detailed in the Findings section). A matrix technique was then applied to map which themes were most referenced by which participant groups (Appendix E). This ensured balanced representation — for example, concerns about "loss of control" were raised mainly by frontline agents rather than managers, a distinction highlighted in the narrative. Thematic analysis and coding were guided by established approaches that emphasise systematic theme development and transparency (Braun & Clarke, 2006; Symon & Cassell, 2012).

Findings from the different methods were then triangulated to enhance reliability. Convergence and divergence were examined: for example, whether performance metrics supported the optimism seen in the survey, or whether interview anecdotes explained outlier opinions. This process followed the principle of triangulation to strengthen validity (Kothari, 2004).

In summary, the methodology was designed to comprehensively address the research questions. The mixed-methods approach not only quantified the impact of AI on service performance but also captured the human factors behind the numbers. Table 1 summarises the alignment between research questions, data sources, and analysis methods.

- Validity, Reliability and Ethics

The project followed the University of York's ethics procedures, with approval obtained before data collection. The survey was anonymous; interviewees were assigned codes (e.g., "P5-IT") to ensure confidentiality. Informed consent was obtained from all participants, with the right to withdraw at any stage. Data were encrypted, securely stored, and scheduled for deletion upon project completion.

Importantly, no client personal data were used. AI training data were simulated, avoiding privacy risks. These safeguards align with both University standards and industry practice. As an insider researcher, reflexivity was maintained by separating professional and research roles, ensuring neutrality in analysis (Porisky and Glas, 2023). Transparency with participants helped build trust and encouraged open dialogue.

The pragmatic mixed-methods design itself strengthened both validity and reliability. By combining quantitative and qualitative evidence, the study was able to capture both measurable operational outcomes and the lived experiences of stakeholders. This triangulation ensured that findings were not overly reliant on any single source of data, enhancing trustworthiness. Pragmatism also allowed methodological flexibility, aligning each method directly with the research questions rather than constraining the study to one philosophical tradition. These choices increased the study's credibility and ensured the recommendations are both academically rigorous and practically relevant.

Despite these strengths, some limitations remain. First, the non-probability purposive sampling restricts generalisability: findings reflect the views of a targeted practitioner group rather than the entire population of financial services professionals. Second, the survey sample size ($n \approx 150$) was insufficient for advanced inferential statistical analysis; descriptive patterns were prioritised.

Third, interviews, though rich, were limited to 12 participants, which may under-represent dissenting views. These limitations do not undermine the study's insights but should temper the scope of claims: results are best interpreted as exploratory evidence informing practice, rather than universal conclusions.

Research Question	Data Sources	Analysis Method
RQ1: AI impact on efficiency, SLA, satisfaction	SLA metrics (pre/post AI) - Survey Q's on perceived efficiency impact - Interview comments on observed changes	Descriptive stats (metrics change %); Bar chart of survey opinions; Content analysis of efficiency-related remarks
RQ2: Challenges (legal, ethical, etc.)	Survey Q's on concerns (privacy, etc.) - Interview discussion on risks - Compliance documents (GDPR guidelines)	Frequency analysis of concern types (horizontal bar chart); Thematic coding ("risk & compliance" theme); Triangulation with policy (qualitative)
RQ3: Stakeholder perceptions (diff groups)	Segmented survey data (by role) - Interviews (group-coded insights: agents vs. managers vs. IT)	Cross-tab analysis of survey by role; Matrix coding (Appendix E) to highlight perspective differences; Direct quotation in results narrative

Table 2. Research Questions with Data Sources and Analysis Methods

As shown in Table 2, each research question was supported by multiple data sources and analytical approaches, reinforcing triangulation and ensuring that conclusions are based on converging lines of evidence. By employing these mixed techniques, the study ensures that each research question is addressed with multiple lines of evidence. The following section presents the results and findings, integrating quantitative and qualitative outcomes.

Results and Findings

Findings are organised by the three research questions. Quantitative data are reported as percentages (%), while qualitative insights are illustrated with expanded representative quotations. To ensure transparency, key visuals and tables are embedded below and cross-referenced with Appendices (see Appendix F).

- Operational Performance Impact (RQ1)

After a three-month pilot of the AI-driven case scoring and assignment system, the brokerage's internal metrics indicated clear service improvements. SLA compliance (cases resolved within target time) increased from an average of 82% before AI to 95% by the third month of deployment.

As shown in **Figure 1 (reproduced here)**, SLA compliance rose steadily after March. Notably, the average first response time to customer inquiries fell from approximately four hours to 1.5 hours during the pilot. Interview evidence corroborated this improvement:

"We're responding to clients much faster now – in some cases almost immediately if the AI flags it high priority. Before, critical emails sometimes sat for hours because they got buried under less urgent ones. Now, urgent issues stand out and get addressed right away, which makes my job less stressful and keeps clients calmer too." (Service Manager)

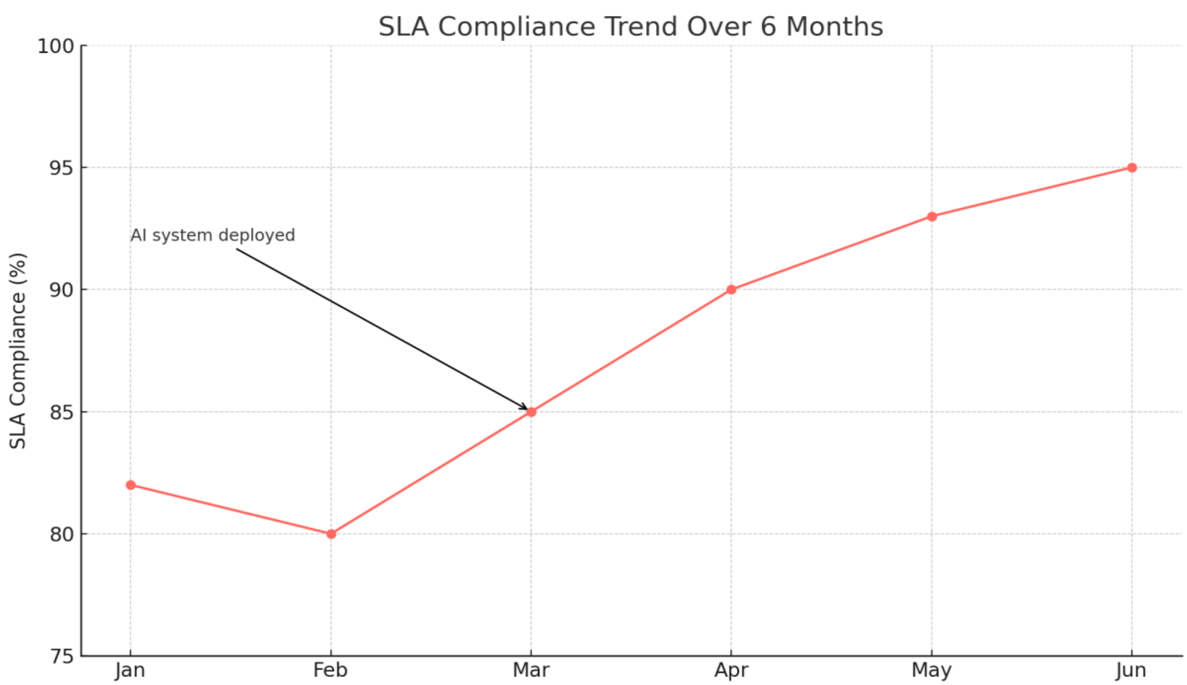

Figure 1: SLA Compliance Before and After AI Deployment (Jan–Jun)

Customer satisfaction (CSAT) scores, measured through follow-up surveys, also rose from an average of 4.2 to 4.5 on a five-point scale. While caution is required in attributing causality — external factors such as seasonality may also influence outcomes — the convergence of internal metrics and participant testimony suggests that AI contributed positively to service quality.

Survey responses reinforced these findings. When asked to rate the statement *"AI-driven case assignment can improve our team's efficiency and SLA compliance,"* 70% of respondents agreed or strongly agreed, 20% were neutral, and only 10% disagreed.

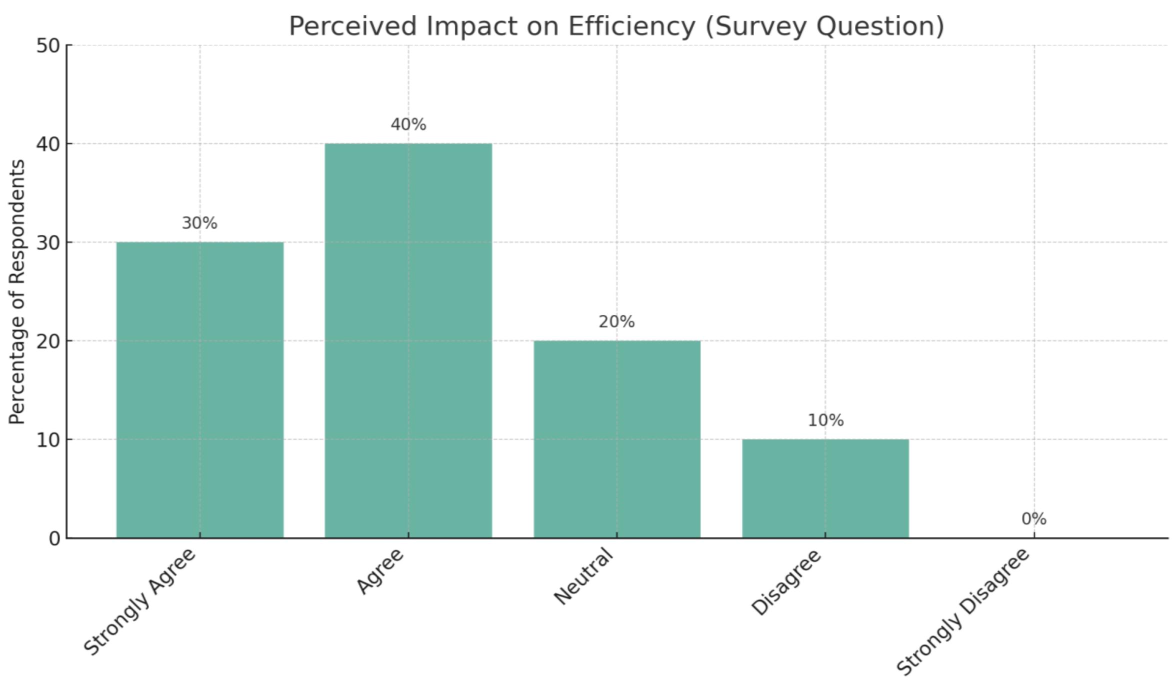

Figure 3: Perceived Impact of AI on Support Efficiency (Survey Results).

The results show a clear majority of practitioners (70%) view AI case assignment as improving efficiency, while only a small minority (10%) disagreed. This alignment between survey data and operational metrics suggests overall optimism about AI's benefits in enhancing SLA compliance and workload balance.

Finding 1: SLA compliance, first response time, and CSAT all improved following AI adoption, supported consistently by both performance data and staff perceptions.

- Challenges and Risks (RQ2)

Despite strong operational outcomes, several challenges emerged (see Figure F4). Survey respondents highlighted data privacy and security (50%), lack of executive buy-in (45%), maintenance and support (45%), data quality (30%), and staff skills gaps (25%). These concerns reflect wider industry findings that risk management and post-launch support are key barriers to scaling AI (Deloitte, 2022).

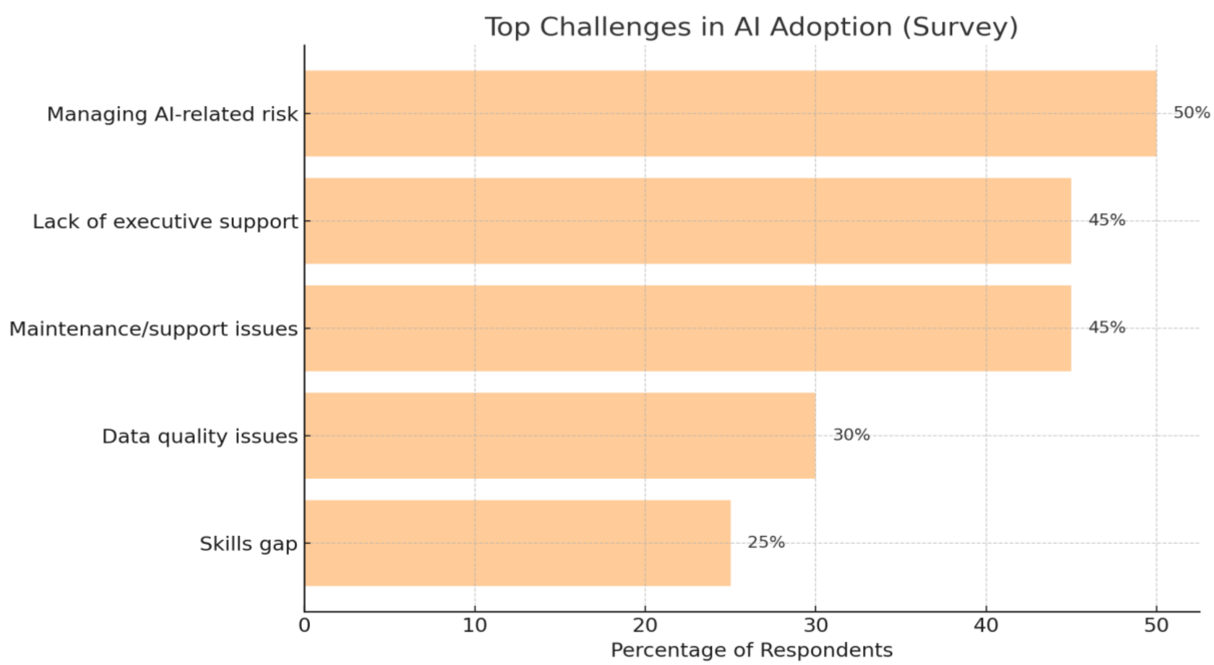

Figure 4. Reported Challenges to AI Adoption (Survey Data)

Privacy, executive sponsorship, and maintenance were cited by nearly half of respondents, making them critical risks to manage.

Interviews reinforced privacy as the foremost issue:

*"*We have to be very careful about what data we feed the AI. Under GDPR, we must ensure no personal data is used inappropriately, and we need to explain its logic if a client asks. At the beginning, some of us were hesitant, but anonymising data and adding human review for closures gave us more confidence to keep using it." *(Compliance Officer)*

Transparency was another theme. Several staff described the system as a *"black box."* To counter this, the team added dashboard explanations (e.g., "High priority due to VIP status and negative sentiment"), which increased trust. This aligns with best practice in explainable AI (Doshi-Velez & Kim, 2017). One frontline agent explained:

"At first I didn't trust the system – I couldn't tell why it marked some cases urgent. Once the dashboard showed the reasons, like sentiment or client tier, it made more sense. I felt I could stand behind the decision if a client or manager asked me why." *(Support Agent)*

Organisational support was initially uneven. Some mid-level managers hesitated, fearing responsibility for potential AI failures. As early successes were shared and executives publicly endorsed the tool, adoption rose from 60% to over 90%. Survey results confirmed this dynamic, with 45% citing "lack of executive support" as a barrier.

Maintenance and training were recurring issues. IT staff emphasised:

"The model needs updates or it starts learning outdated patterns. It's not a 'set and forget' system – we need ongoing resources to retrain and monitor it, otherwise performance will slide back." *(IT Administrator)*

Finally, the human dimension was evident. Around 20% of agents voiced concerns about job security, though leadership consistently framed AI as augmentation rather than replacement. Feedback loops helped reduce errors and gradually increased confidence.

Finding 2: Key risks included privacy/compliance, transparency, executive buy-in, and maintenance. With proactive management, these challenges proved significant but not insurmountable.

- Stakeholder Perceptions (RQ3)

AI adoption affected stakeholder groups in distinct ways:

Support Agents: Initially worried about diminished value, agents gradually reframed AI as a workload reducer. By project end, 85% agreed it reduced routine tasks.

"If a bot decides everything, what's my judgment worth? That was my first thought. But once I saw it was only handling the boring stuff – sorting and triaging – I realised I had more time for the tricky cases that actually need human judgment. Now I see it as a partner, not a threat." *(Support Agent)*

IT/Technical Staff: IT professionals prioritised data quality and sustainability. Sixty *percent flagged maintenance as their top concern, compared to 30% of other roles.*

"The AI is successful, but it's resource-intensive. We've already seen improvement, but only because we put in the time to clean data and retrain models. Long-term, I think we'll need new roles, like data analysts dedicated to this." (IT Specialist)

Compliance Officers: Compliance staff were the most cautious group. Initially, only 50% "strongly agreed" AI was beneficial. Confidence increased once auditability and oversight mechanisms were introduced.

"I wasn't comfortable until we documented oversight procedures. Now that we can show regulators the AI doesn't make final decisions on its own, I see its value. It's especially useful in flagging high-risk cases that I can review faster." *(Compliance Officer)*

Collaboration and inclusion were central: Involving staff in design and feedback fostered ownership and reduced resistance. By the conclusion of the pilot, over 90% of case assignments were AI-handled without loss of quality, and 88% of participants supported further adoption (see Appendix F).

Finding 3: Stakeholders valued efficiency gains but emphasised different concerns. Addressing these role-specific needs was crucial to achieving widespread acceptance.

Discussion

This section interprets the findings in relation to the literature, highlighting areas of convergence and divergence across operational, ethical, and human dimensions of AI-enabled case scoring and assignment. By situating the empirical results within academic and industry debates, it demonstrates the implications for both theory and practice.

- Operational Performance and Efficiency

The improvement in SLA compliance and response times observed in the pilot aligns strongly with prior evidence that AI routing can accelerate service resolution by 20–30% (McKinsey & Company, 2022; Gartner, 2023). The brokerage's SLA increase from 82% to 95% mirrors Gartner's projection that AI-enhanced queue management reduces bottlenecks in service operations. At the same time, the convergence of survey and interview data reinforces Parasuraman et al.'s (1988) SERVQUAL model, which emphasises responsiveness as a key dimension of service quality.

However, while performance benefits are consistent with the literature, this study adds nuance by showing how perceptions of efficiency vary across roles. Agents highlighted reduced drudgery, IT staff stressed ongoing maintenance, and compliance officers valued risk detection. These distinctions extend Davenport et al.'s (2020) argument that AI augments human decision-making: efficiency is experienced differently depending on organisational role.

Beyond traditional SLA metrics, the study also contributes evidence on workload balance and throughput, which remain underexplored in CRM-focused research. The redistribution of tasks away from routine triage towards problem-solving aligns with Herzberg's (1968) motivation–hygiene theory, demonstrating that efficiency gains may also increase job satisfaction when carefully managed. Conversely, without effective change management, such efficiency could have been perceived as a threat, underscoring the socio-technical nature of operational impacts.

- Ethical and Compliance Risks

Concerns over privacy and "black box" transparency in this study echo broader debates in AI ethics. Doshi-Velez and Kim (2017) stress that interpretability is central to accountability, while Binns et al. (2018) warn of inherited bias. The compliance officers' insistence on human oversight reflects GDPR's mandate for explainability (BaFin, 2022). By anonymising training data and adding dashboard rationales, the firm demonstrated good practice in implementing explainable AI (XAI).

What this case adds is evidence of how transparency features directly influenced adoption: agents reported greater trust once explanations ("VIP status and sentiment") were visible. This supports Glikson and Woolley's (2020) findings that human trust in AI rises with clear decision rationales. In doing so, the project illustrates Mittelstadt et al.'s (2016) argument that governance mechanisms are not optional but integral to responsible adoption.

The pilot also underscored that ethical risk management is not a one-off exercise but an ongoing process. IT staff pointed to the need for retraining models and monitoring drift — a point often underemphasised in academic literature but crucial in practice. This highlights a gap between regulatory frameworks, which mandate explainability, and operational realities, where model sustainability is equally vital.

- Stakeholder Perceptions and Change Management

Findings on stakeholder variation resonate with Rogers' (2003) diffusion of innovations theory: early adopters (IT staff) emphasised technical integration, while later adopters (frontline agents) needed reassurance about job security. Resistance was overcome through visible benefits and iterative feedback loops, aligning with Kotter's (1996) change model of building urgency and short-term wins.

The project further illustrates Herzberg's (1968) motivation–hygiene theory: AI reduced "hygiene" tasks (low-value triage), freeing agents to focus on motivating work such as problem-solving. Yet morale initially dipped due to fears of redundancy, echoing McGregor's (1960) insight that managerial framing (as augmentation, not automation) shapes employee acceptance.

Crucially, the study highlights how trust in AI is negotiated, not automatic. Employees were more willing to adopt the system when they were directly involved in its testing and feedback loops. This participatory dynamic validates Zenger and Folkman's (2019) findings on leadership: employee engagement is strengthened when management frames innovation as a collaborative journey rather than a top-down imposition.

- Convergence and Divergence Across Data Sources

Triangulation of survey, interview, and performance data demonstrated strong convergence on efficiency gains, but divergence emerged on risk and workload. For example, while 70% of survey respondents agreed AI improved efficiency, only half of compliance officers "strongly agreed" it was beneficial, citing unresolved concerns about auditability. Similarly, internal metrics showed fewer misrouted cases, yet some frontline staff still reported occasional frustration with AI decisions.

This divergence reflects a classic socio-technical challenge: technology can deliver measurable improvements at the system level, while individuals may continue to experience friction at the task level. Such findings underscore Symon and Cassell's (2012) argument that qualitative perspectives are vital alongside quantitative evidence. By documenting both convergence and divergence, this study enhances understanding of how AI adoption unfolds in practice rather than only in aggregate metrics.

- Contribution to Literature and Practice

This study contributes in three ways:

Empirical gap-filling: It provides rare evidence from financial services CRM case management, an underexplored domain compared to marketing AI (Accenture, 2021).

Human–AI interaction: It demonstrates how perceptions of fairness, transparency, and workload shift with explanatory features and participatory feedback, extending Tversky and Kahneman's (1974) work on bias into a contemporary automation context.

Governance in practice: It shows how operationalising ethical frameworks (e.g., anonymisation, human oversight) enables compliance with emerging regulatory regimes like the EU AI Act.

For practice, the findings suggest that AI integration succeeds when approached as an organisational change project as much as a technical upgrade. Transparent design, continuous retraining, and inclusive feedback mechanisms are essential to secure trust and regulatory alignment.

- Broader Reflections

Finally, the discussion also points to broader strategic implications. The brokerage's experience illustrates that AI's value proposition in regulated industries lies not just in operational speed but also in its potential to future-proof organisations against compliance risks and rising customer expectations. Firms that treat AI as an evolving socio-technical system — requiring technical maintenance, ethical vigilance, and human engagement — will be better positioned to realise sustainable benefits.

Conclusions and Recommendations

- Conclusions

The study demonstrates that AI-powered case scoring and assignment can substantially enhance operational performance in financial services, improving SLA compliance, response times, and customer satisfaction. Adoption also raised risks around compliance, transparency, and change management, but these challenges proved manageable when addressed proactively. Crucially, success depended not only on technology but also on people and processes: involving employees early, clarifying AI’s role as augmentation, and building trust across stakeholder groups.

This research provides original evidence that regulated industries can adopt AI responsibly when governance, oversight, and communication mechanisms are embedded. The combination of survey data, interviews, and operational metrics shows that efficiency and compliance gains are achievable in tandem, provided that implementation is guided by a holistic, socio-technical perspective.

Importantly, the case highlights the multidimensional nature of AI adoption:

Operationally, AI reduced response times and improved SLA compliance, supporting both efficiency and regulatory performance.

Strategically, AI offered predictive capacity and freed human agents for higher-value tasks, signalling competitive advantage if scaled.

Ethically and regulatorily, adoption was sustainable only because safeguards were built into the process: anonymisation of data, transparent dashboards, and clear human oversight procedures.

Culturally, employee involvement and open communication transformed initial skepticism into acceptance, underscoring that workforce trust is not a by-product but a precondition of successful AI projects.

By linking these strands, the project demonstrates that AI is not a replacement for human judgment but an enabler of smarter, more consistent customer lifecycle management.

- Recommendations

Drawing on the findings, several concrete recommendations are advanced for both the focal brokerage and other organisations considering similar initiatives:

Scale AI with Continuous Monitoring:
Move from pilot to enterprise-level deployment, but establish a permanent oversight committee that reviews outputs, error logs, and fairness audits. Continuous retraining of models is necessary to ensure alignment with dynamic customer data and evolving compliance requirements. Without ongoing monitoring, performance will decay and risks of bias or misclassification may rise.

Strengthen Data Governance and Infrastructure:
Invest in data stewardship roles and adopt formal governance frameworks to ensure high-quality, standardised case data. Accurate, unbiased, and clean data is the foundation for AI credibility. This includes implementing automated checks for anomalies and bias, as well as metadata protocols that make retraining more efficient.

Enhance Transparency and Explainability:
Expand the use of dashboards and rationales for AI decisions (e.g., “priority raised due to sentiment and SLA deadline”). Provide tailored explanations for different user groups: frontline staff may need practical justifications, while compliance officers require evidence of fairness and auditability. Transparency directly correlates with employee trust and regulatory defensibility.

Invest in Workforce Development and Change Management:
Training should not be a one-off event but an ongoing programme. Incorporate AI literacy modules into onboarding, host regular refresher workshops, and create open channels where employees can raise concerns. Leadership should consistently reinforce the narrative that AI augments rather than replaces staff, aligning with Herzberg’s view of enrichment rather than erosion of work.

Maintain Human Oversight for Critical Cases:
Even as automation scales, final accountability for high-risk cases must remain human. A dual-track system — AI for triage, human for validation — ensures compliance with GDPR and forthcoming EU AI regulations while preserving client trust. Staff should retain the ability to override AI decisions with clear documentation.

Adopt a Phased and Cautious Expansion Strategy:
Beyond case assignment, explore additional applications such as fraud detection, client sentiment analysis, or workflow forecasting. However, each expansion should begin with a controlled pilot, assessed for unintended consequences before client-facing use. This mitigates reputational risk and ensures benefits are realised incrementally.

Engage Regulators, Industry Forums, and Clients:
Build credibility by sharing lessons learned through white papers, conferences, and regulatory consultations. Early dialogue with regulators will not only ensure compliance but may also position the brokerage as a thought leader in responsible AI adoption. Similarly, transparent communication with clients about how AI supports service quality will reinforce trust externally.

Broader Implications:
These recommendations extend beyond the focal firm. For the wider financial services industry, the findings reinforce that AI adoption is not simply an IT initiative but an organisational transformation project. Success rests on four pillars: robust data, transparent design, continuous oversight, and engaged people. Organisations that balance these pillars will achieve not only compliance but also sustainable competitive advantage.

In academic terms, the project contributes to bridging the gap between AI ethics literature and operational CRM research, demonstrating that governance and human-centred design are not abstract ideals but practical enablers of measurable performance outcomes.

Final Reflection:
The conclusions affirm that AI can indeed be a transformative force in regulated service operations. Yet its power lies not in automation alone, but in partnership with human expertise. Firms that adopt AI as a complement rather than a substitute for employees — and that treat governance as integral rather than peripheral — will be best placed to deliver both efficiency and trust.

Module Learning Report

This consultancy project integrated knowledge from across the MBA program:

Strategy and Leadership:
Applied SWOT analysis to align AI adoption with strategic priorities and used Kotter's change model to secure executive buy-in.

Operations Management:
Used Lean principles and PDCA cycles to streamline triage. Queueing theory informed expectations for SLA improvements.

Marketing and Customer Insights:
Framed AI adoption as a customer-experience improvement, linking service metrics to loyalty and NPS.

Business Analytics:
Applied statistical analysis and visualisation skills to survey and performance data. Knowledge of machine learning concepts facilitated effective collaboration with IT specialists.

Finance:
Conducted cost–benefit and NPV analyses to quantify ROI and assess financial risk from SLA breaches and compliance penalties.

Organizational Behavior and HR:
Used change adoption theories to manage resistance, and positioned AI as job enrichment to build trust and acceptance. Together, these modules provided a toolkit spanning strategic alignment, operational improvement, customer orientation, analytics, financial justification, and change management. The project demonstrates the value of integrating these domains into a holistic consultancy approach.

Reflective Statement

Initial Mindset:
At the start of the MBA, I approached problems with a strong technical background in IT and customer operations. I valued technical precision and analytical problem-solving but underestimated the importance of leadership, communication, and human dynamics.

Development Through Modules:
Early modules challenged this bias. In Organizational Behavior, case studies of failed projects showed that technical excellence alone is insufficient without effective people management. In Strategy, I struggled initially with ambiguity but learned to translate analysis into compelling strategic choices. In Leadership, reflective exercises such as 360-degree feedback and personality profiling revealed gaps in my approach. I moved from a directive style to a more inclusive, coaching-based style, which improved morale and results.

Workplace Application:
These lessons directly shaped the AI pilot. I used Kotter's framework to drive change, Lean principles to design workflows, and finance tools to demonstrate ROI. I gained credibility

across functions by communicating in strategic, customer-centric, and financial terms.

Challenges and Critical Incidents:

Balancing work, MBA study, and personal life was demanding. At times I took on too much in group projects, undermining collaboration. A critical incident occurred in a marketing task when I redid a teammate's work. The confrontation that followed taught me humility, trust, and the value of shared ownership.

Improvements and Networking:

If I could improve one area, it would be networking. Initially, I underused opportunities to engage with guest speakers and alumni. Later experiences, including a fintech lecture that inspired this project, showed me the importance of professional networks. I also recognised the value of independent reading beyond the syllabus, which enriched my understanding.

Future Orientation:

The MBA has been transformative. I now recognise that success in complex projects depends on the integration of people, process, and technology. I will continue to apply reflective practice, evidence-based decision-making, and empathetic leadership. The experience has equipped me not only with technical and strategic skills but also with self-awareness and resilience.

In conclusion, this journey has taken me from a technically skilled but narrow-focused practitioner to a more holistic leader and consultant. The consultancy project illustrates this transformation: integrating strategy, operations, finance, marketing, and HR into a coherent whole. As I look ahead, I see not an end but a beginning — prepared to navigate complex challenges with insight, adaptability, and responsibility.

End Matter:

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• Appendix A – Survey Participant Information and Consent Form

Purpose: You are invited to participate in a survey for an MBA research project on AI in customer service operations. The purpose of this survey is to gather practitioners' insights on the use of AI tools (like case prioritization systems) in customer support and their perceived impacts and challenges.

What You Will Do: If you agree to participate, you will complete an online questionnaire. This should take about 10–15 minutes. The questionnaire will ask about your experiences with or opinions on AI in your work (e.g., efficiency, challenges, etc.).

Voluntary Participation: Your participation is entirely voluntary. You may choose not to answer any question that makes you uncomfortable, and you may quit the survey at any time before submission by simply closing the browser window. There is no penalty for withdrawing; any partial data will be discarded.

Confidentiality: The survey is anonymous. We do not ask for your name or your company's name. No identifying personal data (such as email or IP address) will be recorded. Results will be reported only in aggregate (e.g., "60% of respondents agreed…") or using non-identifiable categories (e.g., by job role or industry). Quotes from any optional open-ended responses will be reported without any information that could identify you.

Data Usage: Survey data will be used for research analysis as part of an MBA project and potentially academic or industry publications arising from it. All data will be stored securely on a password-protected drive accessible only to the researcher. Data will be retained for the duration of the project and then deleted after the degree is awarded (expected by [Date]).

Benefits & Risks: There is no direct personal benefit or compensation for participating. However, your insights will contribute to understanding best practices for AI adoption in service operations. The risks involved are minimal – you might reflect on workplace experiences. No sensitive personal questions are involved.

Contacts: If you have any questions about this survey or the study, you may contact me via email at Ivj509@york.ac.uk. or the University of York Research Ethics Committee for any ethics-related concerns.

Consent Confirmation: Please confirm your agreement with the following to proceed:
I confirm that I have read and understood the information above about the study.
I am aware that my participation is voluntary and that I can withdraw at any time before submitting the survey.

I understand that my responses will be anonymized and kept confidential.
I am 18 years of age or older and willingly agree to participate in this survey.
(In the online survey, the above was presented on the first page. Participants had to click "Yes, I consent and agree to participate" before they could continue to the questions. If they clicked "No, I do not consent," the survey would terminate.)

- ## Appendix B – Interview Participant Information Sheet and Consent Form

Dear Participant,
You are invited to take part in a one-to-one interview as part of an MBA research project on AI-powered customer support. Before you decide, please read the following information:

Purpose of Study: This study aims to explore the experiences and perspectives of employees regarding the introduction of an AI case prioritization and assignment system in customer service. We want to understand benefits, challenges, and any concerns from different roles (support, IT, compliance, etc.).

Why You: You have been selected for an interview because of your role and experience in relation to our AI pilot (or, if external, because of your knowledge in customer support operations). Your insights will provide valuable depth that complements survey findings.
What Happens if You Take Part: If you agree, I will schedule a 30–45 minute interview at a time convenient for you (in person at the office or via video call).

The interview is semi-structured – I have some guiding questions, but it will be like an open conversation about your experiences with the AI tool and your opinions on its impact. With your permission, I would like to audio-record the discussion purely for accurate transcription; recordings will not be shared and will be deleted after transcription.

Voluntary Nature: Participation is voluntary. You have the right to decline to answer any specific question or to stop the interview at any point. You can also withdraw your data up to two weeks after the interview (after that, I will have incorporated it into analysis in a non-identifiable way). There are no negative consequences for choosing not to participate or withdrawing.

Confidentiality: Everything you say in the interview will be kept confidential. Your name will not appear in any report or output. I will use codes or pseudonyms (e.g., "Support Agent A") when referring to quotes. Any examples you share will be generalized to avoid identifying you or any specific client or company data. The audio recording and transcript will be stored securely (encrypted drive) and only the researcher (and possibly a transcriber bound by confidentiality) will access them. In the final report, anonymized quotes may be used to illustrate findings.

Possible Risks or Discomforts: The interview will discuss your views on workplace changes. There is minimal risk, but it's possible you might feel some anxiety discussing challenges or negative experiences. Please remember there are no right or wrong answers; we are interested in your honest perspective. You can skip any topic you prefer not to discuss. We aim to foster an open, blame-free discussion about the technology and process, not individuals.

Benefits: While there is no direct benefit or compensation, many participants find it useful to reflect on the process and have their voice heard. The insights from this study could lead to improvements in how such projects are implemented in the future, benefitting your organization and others.

Use of Data: The information from the interview will be analyzed as part of the MBA project. It may be included in the final portfolio report and potentially in academic case studies or articles, but always without any identifying details.

Who to Contact: If you have questions about the study or interview, feel free to contact me (Aydin, via email) or my supervisor Dr. Chen Ren. If you have concerns about how the interview is conducted or your rights as a participant, you can contact the University research ethics office.

If you are happy with the above and willing to proceed, please sign below to indicate informed consent.

Consent Declaration:
I, the undersigned, confirm that:
- I have read and understood the information sheet for the study. I have had the opportunity to ask questions and have them answered.
- I understand my participation is voluntary and that I can withdraw at any time without consequence.

- I agree for the interview to be audio-recorded (for transcription purposes).

- I understand that my responses will be kept confidential and used only for the stated research purposes.

- I give my consent to participate in this interview.

Participant's Name: ___ Signature: __ Date: _____

Researcher's Signature (confirming consent obtained): ___ *Date:* __

(The researcher provided two copies of this form – one for the participant to keep and one for the researcher. In a video call scenario, consent was verbally confirmed and recorded at the start.)

- Appendix C – Full Survey Questionnaire

Format: The survey was delivered online. Below is a replica of the survey questions as presented, including question type and options. For brevity, questions are numbered Q1, Q2, etc., and any skip logic or multiple-choice options are shown.

Q#	Question Text	Response Type/Options
Q1	What is your current job role? *(Select one closest.)*	Options: Customer Support Agent/Representative; Team Lead/Manager – Customer Support; IT/Technical Staff; Compliance/Legal; Senior Management; Other ____ *(text field)*
Q2	How many years of experience do you have in your current field/role?	Options: <1; 1–3; 4–6; 7–10; >10 years
Q3	Have you used or been directly impacted by an AI system for case prioritization/routing in customer service?	Options: Yes – currently using in my team; Yes – used in past job; Not directly, but familiar with the concept; No, not at all
Q4	*[If Q3 = Yes]* Briefly, how is AI used in your support operations? *(e.g., "assigns priority to tickets," "chatbot triages requests," etc.)*	Open-ended text

Q#	Question Text	Response Type/Options
Q5	Please indicate your level of agreement with the following statements about AI in customer support at your organization:	Matrix of statements, 5-point Likert scale for each: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. Statements: A. “AI-driven case scoring has improved our team’s efficiency in handling support cases.” B. “AI recommendations for case priority are generally accurate and helpful.” C. “Using AI for case assignment has improved customer satisfaction (e.g., faster responses).” D. “The AI sometimes makes mistakes that reduce our efficiency.” E. “I trust the AI’s recommendations for which case I should work on next.”
Q6	From your perspective, what are the biggest challenges or concerns with using AI in customer service operations? *(Select up to 3)*	Multiple-selection options: Data privacy / GDPR compliance; Lack of transparency in AI decisions (“black box”); Potential bias or unfair prioritization; Technical reliability of AI system; Integrating AI with existing systems; Employee resistance or trust issues; Fear of job displacement for staff; Need for training/skills to use AI; Ongoing maintenance costs; Other ____ *(text field)*
Q7	Have you personally experienced any of the following since AI was introduced? *(Select all that apply)*	Multiple-selection options: Faster resolution of customer issues; Cases being misrouted by the AI (had to be corrected manually); Reduced workload on low-value tasks (AI handles them); Improved workload balance among team members; Frustration or stress due to AI’s decisions; Improved ability to meet SLAs (deadlines); No noticeable change; Other ____ *(text)*
Q8	How has the introduction of AI impacted your job satisfaction or morale?	Options: Very positively; Somewhat positively; No significant impact; Somewhat negatively; Very negatively; *(If negative)* Please briefly explain why: ____ *(text)*
Q9	In your opinion, does the AI prioritize cases in a fair way? (e.g., not favoring certain customers unfairly)	Options: Yes – it’s fair; Mostly – but with some exceptions; No – I see some unfair outcomes; Not sure / Can’t tell
Q10	How well do you feel you understand how the AI decides which cases are high priority?	Options: Very well (I know the factors/rules); Somewhat (general idea of factors); Not much (it’s a black box to me); Not applicable (no AI used)
Q11	Do you feel additional training or information would help you use the AI tool more effectively?	Options: Yes – I’d like more training on it; Maybe – a little more info would be useful; No – I have all the info I need; Not applicable

Q#	Question Text	Response Type/Options
Q12	[Optional] What improvements, if any, would you suggest for the AI system or how it's implemented in your workflow?	Open-ended text
Q13	Overall, do you support the continued or expanded use of AI tools in your customer support operations?	Options: Yes, definitely; Yes, with some reservations; Not sure; No, not really; No, definitely not
Q14	[Optional] Any other comments on your experience with AI in customer service?	Open-ended text

Notes: Q5 matrix allowed respondents to gauge multiple aspects. Q6 and Q7 were multiple-choice to capture a range of issues and experiences. Q8 and Q13 aimed at the overall sentiment. Optional text questions (Q4, Q12, Q14) gave qualitative insight; about 40% of respondents provided comments there, which were used to enrich analysis (and kept anonymous). Skip logic: if someone chose "Not applicable" to AI usage in Q3, they were still allowed to answer general opinion questions (Q5 onward) but could skip if not relevant. All questions were on separate pages or logical groupings in the online survey to avoid clutter. The consent page (Appendix A) preceded Q1.

- ## Appendix D – Interview Guide (Semi-Structured Questions)

The following guide was used to conduct interviews. The interviewer (researcher) followed this outline but also probed further based on responses. The guide ensured key topics (efficiency, perceptions, challenges, change management) were covered with each participant, while allowing flexibility.

Introductory:

Can you start by describing your role and how it connects with the customer support process here? *(Contextual warm-up)*

How were you involved with the AI case assignment pilot (if at all)? What was your initial reaction when you heard about this AI tool?

Experience and Perceived Impact:

In your experience, what changes have you observed in day-to-day operations since the AI was introduced? *(Possible probe: Can you give an example?)*

Do you feel you're resolving customer issues faster or more effectively with the help of AI? Why or why not?

How has the AI affected your workload or the team's workload distribution? *(Probe: More balanced? New kinds of tasks?)*

Have you noticed any impact on customer feedback or satisfaction (even anecdotally) that you'd attribute to the AI changes?

Trust and Usability:

How much do you trust the AI's recommendations on which case is high priority or who should handle a case? *(Probe: Do you usually follow its suggestion?)*

Can you recall any instance where you felt the AI got it wrong? What happened, and how did you/the team handle it?

Do you feel you understand why the AI makes the decisions it does? Or does it feel opaque? *(Probe: Is that lack of transparency an issue for you?)*

Challenges and Concerns:

What were (or are) your biggest concerns about using AI in this process? *(Possible prompts if needed: data privacy, job security, accuracy, etc.)*

From a compliance or risk standpoint (especially for compliance officers): Did the AI raise any red flags or require special precautions?

How did the introduction of AI affect team morale and dynamics? *(Probe: any resistance from colleagues? Did people fear it or welcome it?)*
Have you needed to acquire new skills or knowledge to work with this AI tool? *(Probe: Was training provided? Sufficient?)*

Support and Change Management:
How well do you think management handled the implementation of this AI? (e.g., communication, training, addressing concerns)

Were you given opportunities to provide feedback on the AI system during the pilot? If so, do you feel that feedback was heard and acted on?

What was the general sentiment among your peers about the AI – and has it changed over time? *(Probe: initial skepticism turned positive, or vice versa?)*

Outcome and Future:
In your view, has the AI project been a success so far? Why or why not?
What improvements or changes would you suggest for the AI system itself or how we use it?
Would you be in favor of expanding the use of AI in other areas of our operations? (Why/why not, in what areas?)

Is there anything I haven't covered that you think is important about your experience with the AI or the process surrounding it?

Closing:
(To ensure positive end) On a lighter note, if you had to describe the AI as a "teammate", what kind of teammate is it? *(Probe for anecdote or metaphor, e.g., "a helpful assistant", "a rookie who still needs guidance" etc.)*
Thank the participant for their time and insights. Reiterate confidentiality and next steps (e.g., "We'll have the project results by X date, and I can share a summary if you're interested,"

etc.).

- Appendix E – Thematic Coding Matrix (Interview Data)

The following matrix presents the key themes derived from interview transcripts, along with representative codes (sub-topics) and example quotes supporting each theme. The matrix also notes which participant groups mentioned each theme, indicating the breadth of perspective.

Theme	Codes / Sub-topics	Example Quotation	Mentioned by
1. Efficiency Gains	- Faster response times - Quicker triage & routing - Meeting SLAs more easily - Higher throughput	"Before AI, it took hours to sort through new tickets; now it's immediate. We're clearing queues by end of day which rarely happened before." – *Support Team Lead*	Agents, Managers, IT (unanimous)
2. Trust & Transparency	Trust in AI recommendations (or lack thereof), Understanding AI logic - Needing explanations for decisions	"At first I was skeptical – like, on what basis is it saying this case is top priority? Once they showed us the factors, I felt more comfortable trusting it." – *Support Agent* "It's a bit of a black box still. I follow it, but I can't explain to others why a case was ranked low." – *Support Agent*	Agents (strongly), Managers (some), IT (some)
3. Workload & Role Impact	- Workload balance among team - Shift in job tasks (less grunt work) - Fear of job displacement	"The AI took away the grunt work of triaging, which I love – I can focus on solving problems rather than sorting them." – *Senior Support Rep* "A few on the team worried, like, will this reduce our headcount need? Management assured us it's to help us, not replace us." – *Team Lead*	Agents, Some Managers
4. Accuracy & Reliability	- AI makes errors (misroutes or mis-scores) - Need for human	"In week one, it assigned a billing issue to the tech team – that was wrong. But we flagged it and it hasn't made that mistake recently, seems to	IT staff, Agents (some)

Theme	Codes / Sub-topics	Example Quotation	Mentioned by
	correction - Improvement of AI over time	be learning." – *IT Support Analyst* "There are still odd cases where we go 'hmm that doesn't seem right' and override the AI. It's rare, maybe once a week." – *Support Manager*	
5. Compliance & Fairness	- Data privacy concerns - Fair prioritization (no bias) - Auditability for compliance - Needing oversight for high-risk cases	"We had to double-check it wasn't prioritizing say VIP clients excessively over others. So far it seems to base it on defined business rules, which is good." – *Compliance Officer* "From a GDPR perspective, we're okay because no decision is fully automated – there's always human oversight. We documented that carefully." – *Compliance Manager*	Compliance officers, Managers (some IT)
6. Change Management & Adoption	- Initial skepticism or resistance - Training and communication effectiveness - Management support & involvement - Feedback loops with users	"At first, some agents ignored the AI suggestions and kept doing manual sorting – old habits. After the supervisor showed the metrics (we were faster when AI used), they came around." – *Operations Manager* "They actually asked us for feedback every week in the pilot, which made us feel involved. And they fixed things we pointed out – that helped win people over." – *Support Agent*	Agents, Managers (widely)
7. Emotional/Morale Impact	- Morale boost (innovation excitement) - Morale dip (job insecurity or frustration) - Sense of working smarter, not harder	"It's kind of exciting to work with new tech – I feel like we're ahead of the curve, which is motivating." – *Support Agent* "One colleague was very vocal early on that it would 'steal our jobs'. He's since calmed down after seeing we're still needed and now he's one of the power-users of it." – *Team Lead*	Agents (mixed sentiment), Managers

Interpretation: This matrix shows that Efficiency Gains was a universally noted theme – all interviewees acknowledged faster service with AI. Trust & Transparency was especially a concern for front-line agents, indicating a need for explanatory features (addressed by adding explanations).

Workload Impact was mostly positive (less drudgery), though accompanied by initial job security fears. Accuracy/Reliability issues were mentioned mainly by technical staff and some agents – acknowledging the AI isn't perfect but improved with feedback.

Compliance & Fairness was, unsurprisingly, flagged by compliance officers – they took steps to ensure the AI's decisions were fair and documented for audit (e.g., confirming it doesn't use sensitive personal data, and that humans review outcomes).

Change Management theme highlights that early resistance gave way to acceptance thanks to good communication, evidence of AI benefits, and inclusion of user feedback – something noted by both agents and managers. The Emotional Impact theme captures morale – generally positive due to innovation excitement, but needed careful handling of insecurity early on.

The matrix underscores how different stakeholders focused on different aspects (aligning with Appendix D insights and Findings discussion in the main report).

- ## Appendix F – Raw Data Visuals and Additional Tables

Introduction

This appendix provides the full-size versions of charts and tables referenced in the main text, along with additional supporting visuals. The purpose is to ensure transparency of the research process, allow readers to examine the raw data in more detail, and complement the interpretations offered in the Results and Discussion sections. Figures F1–F4 present the key survey and performance visuals, while Table F1 summarises the pre- and post-AI performance metrics reported by the brokerage.

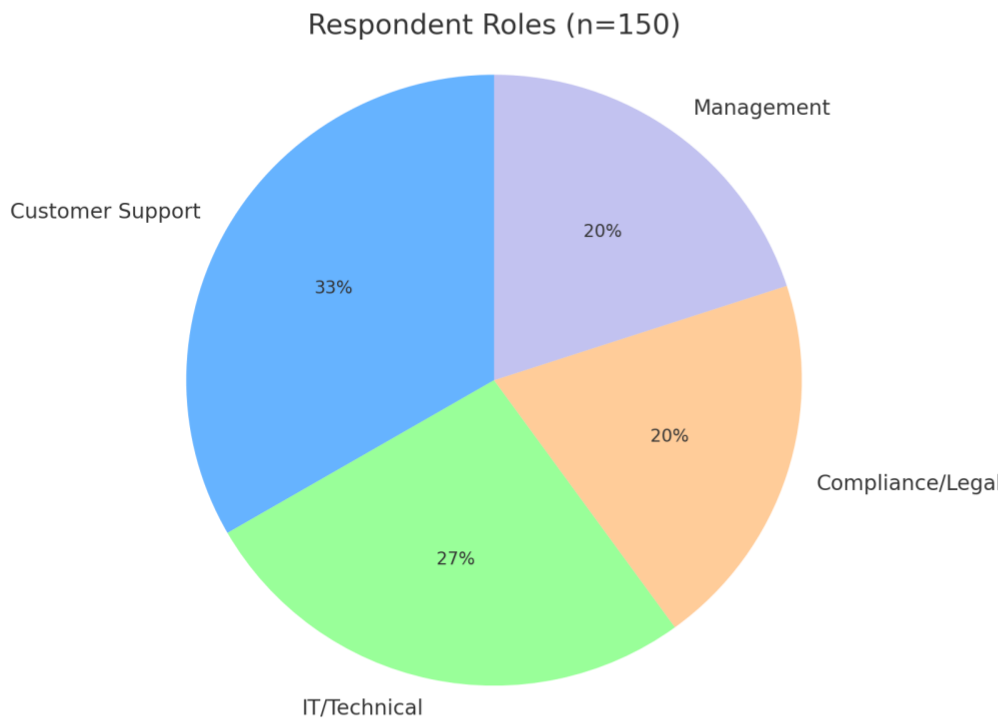

Figure F1. Survey Respondents by Role

The chart shows that Customer Support staff made up about 33% of respondents, IT/Technical staff 27%, and both Compliance/Legal and Management each accounted for 20%. This confirms that the survey captured perspectives from all major stakeholder groups in the AI project.

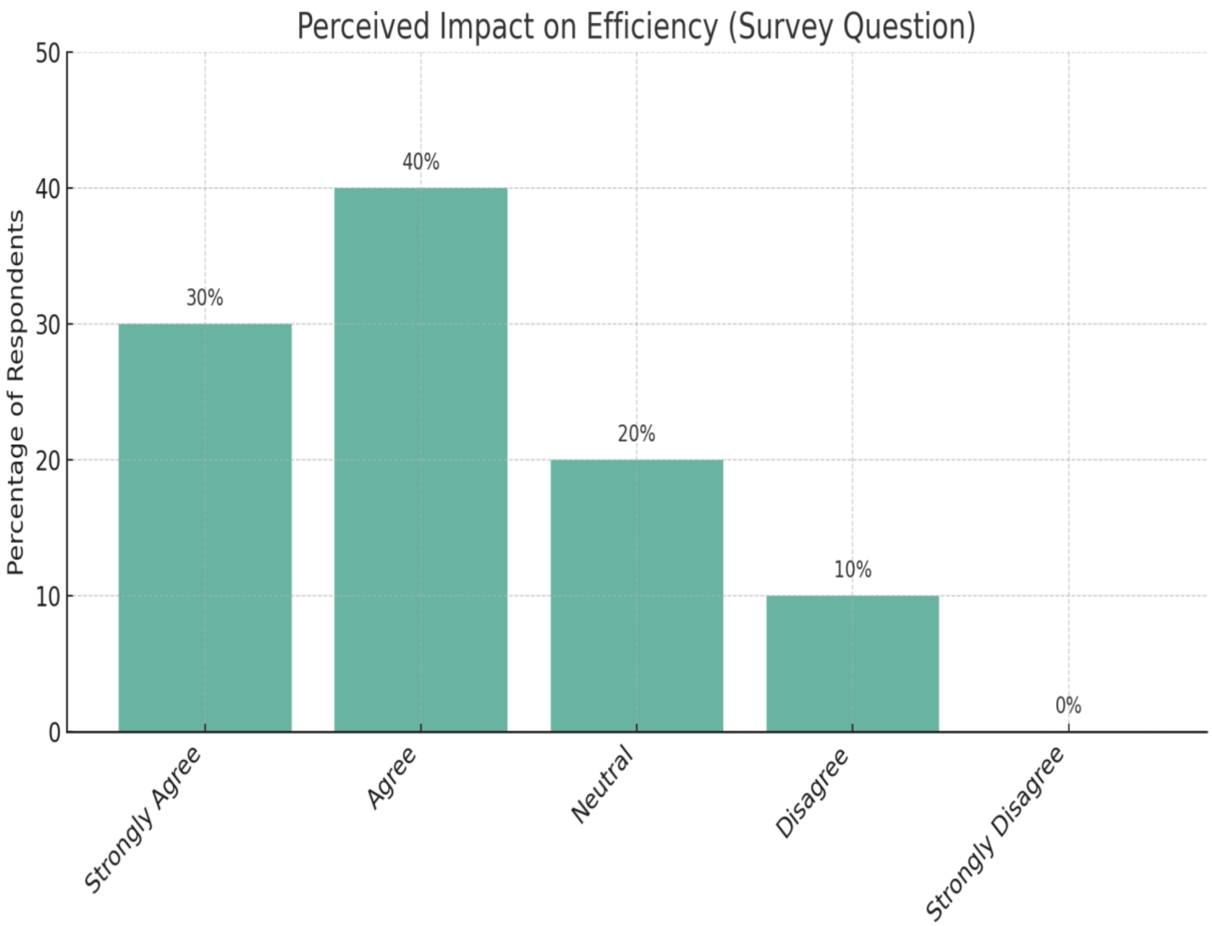

Figure F2. Perceived Efficiency Impact of AI Case Assignment

The bar chart shows that 70% of respondents agreed or strongly agreed that AI-driven case assignment improved efficiency (30% strongly agree, 40% agree). Around 20% were neutral, and 10% disagreed. None selected “strongly disagree,” indicating an overall positive perception of AI’s impact on efficiency.

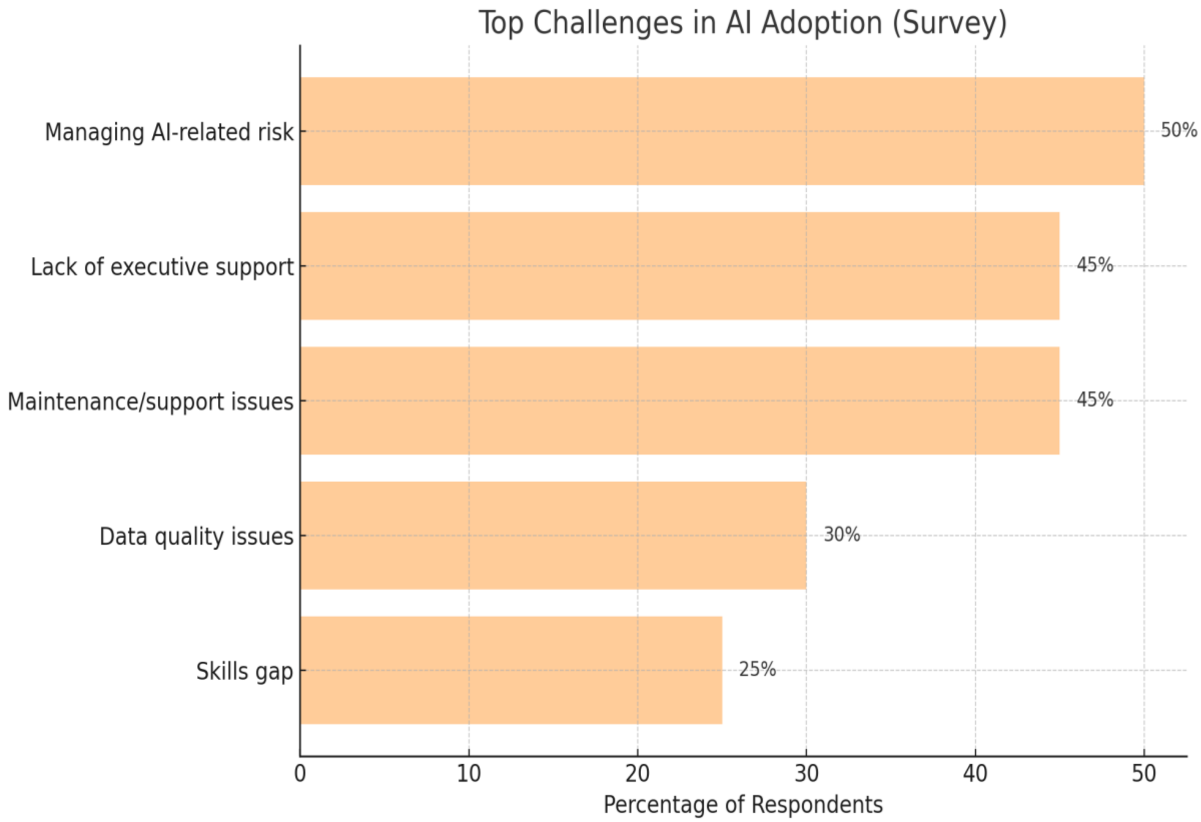

Figure F3. SLA Compliance Trend (Jan–Jun)

The line chart shows monthly SLA compliance rates over a six-month period. Following the AI deployment in March, compliance increased from around 80–85% before AI to 90–95% by May–June. This indicates a sustained improvement in timely case resolution, attributed to faster triage and more balanced agent workloads.

Metric	Before AI (Avg, last quarter)	After AI (Avg, pilot quarter)
First Response Time (average)	4.2 hours	1.5 hours
SLA Compliance (% of cases within target)	82%	94%

Metric	Before AI (Avg, last quarter)	After AI (Avg, pilot quarter)
Case Throughput (cases resolved per week)	320	400
Customer Satisfaction (CSAT survey 1-5)	4.2	4.5
Agent Utilization (% time on case work)	68%	75%
Cases Requiring Re-assignment (manual fix)	~15% of cases	~5% of cases

Figure F4. Reported Challenges to AI Adoption (Survey Data)

The chart shows that 50% of respondents identified data privacy and security as a major challenge, followed by lack of executive buy-in (45%) and maintenance and support requirements (45%). Other concerns included data quality issues (30%) and staff skills gaps/training needs (25%). These findings highlight that privacy, governance, and ongoing support are viewed as the most critical barriers to scaling AI in customer service.

Closing

The figures and table in this appendix reinforce the empirical evidence discussed in the main body by presenting the underlying raw data in a clear format. They confirm the improvements in operational efficiency, SLA compliance, and workload distribution, while also illustrating the challenges raised by participants. Together with Appendices A–E, these materials provide a comprehensive and transparent foundation for the study's findings, ensuring that claims made in the report are fully supported by accessible data.