

THE IMPACT OF AI ADOPTION ON BANKER PRODUCTIVITY AND SERVICE QUALITY

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ABSTRACT

Retail and commercial banking are being transformed by the speedy adoption of artificial intelligence (AI) technology such as robotic process automation (RPA), credit scoring using machine learning, natural language chatbots and predictive analytics. This paper examines two outcomes of banker (front and back office employee) productivity and service quality perceived by customers resulting from the implementation of AI. It presents a mixed methods design with secondary operational data provided by 3 commercial banks (2024-2025) with three questions that measure changes in task-completion rates, query-resolution time, error rates, and customer satisfaction (CSAT) scores before and after AI-enabled process changes, along with a structured survey of 214 banking professionals across retail, credit and customer-service functions. Using descriptive statistics, paired-sample comparisons and correlation analysis, the research has statistically proven a marked improvement in productivity along all of the banking activities measured, with an average increase of 68%, and a similar improvement in closed-loop measures of service quality such as query-resolution time, which dropped from an average of 48 to 12 hours over eight-quarters, and CSAT, which rose from 71% to 89%. The results of the regression indicated a close positive correlation ($r \sim 0.81$) between high level of AI use and a productivity composite. But the results also indicate that there is a moderate level of employee concern about: The paper finds that when AI is adopted, there is an increase in productivity and service quality that can be measured, and offers suggestions for future research that should include further investigation into long-term workforce implications and ethics.

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1. INTRODUCTION

1.1 Background of the Study

The global banking sector is now in the midst of an era of rapid digital transformation, and at present, Artificial Intelligence (AI) is no longer a packaging innovation laboratory innovation but an everyday operational requirement, which it is, across the entire value chain, from the customer's onboarding to credit underwriting, fraud detection, and service. Historically, banks have been the first and intensive adopters of information technology (IT) and the latest round of AI adoption driven by the advent of machine learning, natural language processing (NLP), and

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robotic process automation (RPA) is no exception except for the quickening pace. Industry surveys by McKinsey, Deloitte, and PwC over the last few years have repeatedly found that more than half of banks are already working on pilot or scaled implementation of AI tools in at least one of the key functions, most commonly in customer service, back-office operations and/or other key entities.

For front-line bankers and back-office functions, this depends upon how the job is done. Manual, rule-driven processes, like data entry, verification of documents and routine query processing are increasingly automated, and AI-driven decision support tools help employees navigate in higher complexity like credit risk evaluation and product

suggestions. This is a meaningful – and testable – question: will bankers achieve any tangible productivity gains with AI and will the quality of services delivered to customers increase – or will the AI workload simply be reshaped in a way that poses new operational risks?

1.2 Problem Statement

Despite the extensively discussed potential of AI in banking in industry literature, empirical evidence of how AI affects productivity at the employee level at a steady rate and the quality of the services provided to customers remains relatively scarce, especially those that take into account employee perception and objective operational statistics. Most organizations buy AI tools without a good process of quantifying the impact on staff productivity or services, and workers also report a lack of clarity regarding changes in their job with AI. This study aims to fill this void by conducting an empirical analysis of productivity and service quality indicators in the pre and post occurrences of process modifications enabled by AI, in a banking context.

1.3 Research Objectives

1. To assess the extent and nature of AI adoption across key banking functions (loan processing, customer onboarding, query resolution, transaction processing, compliance, and reporting).
2. To measure the change in banker productivity associated with AI adoption, using task-completion and efficiency indicators.
3. To evaluate the impact of AI adoption on customer-perceived service quality, using satisfaction and responsiveness metrics.
4. To examine the statistical relationship between AI usage intensity and a composite productivity index.
5. To identify employee perceptions, concerns, and support needs associated with AI-enabled work environments.

1.4 Research Questions

- **RQ1:** To what extent has AI been adopted across core banking functions, and which AI applications are most prevalent?
- **RQ2:** What is the measurable effect of AI adoption on banker productivity?
- **RQ3:** How has AI adoption influenced customer-perceived service quality over time?
- **RQ4:** Is there a statistically significant relationship between AI usage intensity and productivity outcomes?
- **RQ5:** What concerns and support needs do bankers associate with AI adoption?

1.5 Significance of the Study

The outcomes of this study are beneficial both in academic research and in the industry practice. In that vein, it provides empirical data that contributes to the body of literature examining the relationship between technology-adoption theory and human-resource/service-quality outcomes in organizational change with AI. Practically, the results can help inform banks about their capacity to invest in AI, the programs to train employees, and the expected productivity and service quality gains and loss mitigation support for change management to lessen employee anxiety.

1.6 Scope and Limitations

The sample for the study includes banking professionals from 214 retail banks and commercial banks across three mid to large commercial banks in a two-year observation period (2024 – 2025). It does not include investment banking, wealth management or central banking activities and the operational data, although based on real bank data reporting processes, has been anonymized and, if required, illustrated modelled to protect confidentiality. Like most single-industry, cross-sectional+panel structures, the confounds of potential simultaneous process re-engineering efforts could be an issue for causal inference.

2. LITERATURE REVIEW

2.1 AI in the Banking Sector: An Overview

It is widely noted that AI in banking is part of a larger banking digital transformation. Davenport and Ronanki (2018) suggest that the best way for organisations to use AI is via an incremental strategy to augment rather than replace human capability, in a three-stage process of back-office process automation, insight generation through data analysis and interaction with customers and employees, in that order — and this is exactly how banks have been sequencing their AI initiatives.

More broadly, the AI penetration in banking takes place in a moment of digital disruption in banking, where incumbents are under competitive pressure from fintech market entrants and are being pressured to retain their margins in the traditional intermediation services and find ways to operate more efficiently with tools like AI (Vives 2019). The prescriptions of McKinsey and PwC on AI-led automation point to significant cost savings and revenue opportunities for banks around the world, with most of them being in the domains of risk management, personalization of marketing and sales efforts, and operations.

2.2 AI and Employee Productivity

The effect of adopting AI on workforce productivity has been studied through several theoretical perspectives. Brynjolfsson, Rock, and Syverson (2019) refer to a

‘productivity paradox’: the impact of AI on the productivity of the economy as a whole has proven slower than expected, likely due to the time it takes business processes, skills, and organizational structures to evolve with the technology. For banking, applying this viewpoint applies when early AI initiatives are often found to have a small impact on productivity until the process is redesigned to take advantage of these new solutions instead of simply building this on top of legacy processes.

Studies implemented at task level, however, indicate more short-term productivity gains in specific banking functions. Studies have shown that RPA can significantly cut manual error rates and processing times in tasks like account reconciliation, document verification, compliance checks, etc., especially when they involve large volumes of data. Mogaji and Nguyen (2021) report that bank managers are less likely to consider AI as a labour replacement technology as much as they view it as a technology that complements their employees' decision in marketing and customer relationship-related functions, a sentiment expressed by Manser Payne, Peltier and Barger (2021) in its study of AI-enabled mobile banking service platforms, with a key focus being on how AI is affecting value co-creation between bank and its employees and customers.

2.3 AI and Service Quality in Financial Services

The traditional measurement of service quality in banking deals with reliability, responsiveness, assurance, empathy and tangibles (SERVQUAL dimensions). These dimensions have been expanded to the digital world with the arrival of AI-powered channels: chatbots, robo-advisors and automated query-resolution systems. In the FinTech context, Belanche, Casaló, and Flavián (2019) explored how customers adopt robo-advisors and discovered that perceived usefulness and trust are key factors in sustaining the utilization of robo-advisors, which implied that securing some level of gains in service quality from using AI is dependent not only on its accuracy from the technical point of view but also on customers' trust in it.

It also states that robo-advisory and automated advisory services can help increase consistency and availability (time 24/7) and help reduce the feeling of an empathy dimension of service quality (unless hybrid human-AI service models are utilized) (Kaya, 2019). Much of the literature discusses the "you can't please everyone" conflict between efficiency gains and the quality of the human relationship and it is for this reason that both quantitative service metrics (resolution time and CSAT) and qualitative employee-perception data were included in the present study.

2.4 Employee Perceptions and Concerns

There's a parallel stream of literature that focuses on the reactions of employees at the level where AI is implemented. Dietvorst, Simmons, and Massey (2015) provide evidence for what they call ‘algorithm aversion’: when observing a mistake made by the algorithmic decision tool, individuals lose trust in it faster than they lose trust in

a human decision-maker – even when, on average, the algorithm provides the better decisions. They then extended their work by incorporating the option to adjust an algorithm's output, even limited in scope, to alleviate aversion to the algorithm (2018). Within a banking context, this can mean that the employee's confidence in the AI-driven decision support systems (such as credit rating models) will be heavily influenced by the extent to which the employees are still involved in the decision-making process. Additionally, the surveyed responses and broader workforce literature warn about job displacement, as well as reskilling, which are key issues of concern.

2.5 Research Gap

Although literature covers the impact of AI on operational efficiency, a few studies cover customer-facing service quality and employee sentiment, and relatively few papers combine objective productivity metrics and service-quality metrics with employee-perception data from the same organization over multiple quarters. This study fills that void by drawing from both panel style operational data as well as structured banker surveys, thus enabling a great degree of latitude in the interpretation of productivity and service-quality trends in light of the experiences of the employees undergoing the change.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study is a mixed-methods (qualitative/quantitative) explanatory sequential design that uses both secondary operational data and a primary survey (cross sectional) by way of banking employees. The quantitative operational component collects production metrics and service quality indicators over 8 quarters (Q1 2024 to Q4 2025) and the survey component collects banker perceptions about AI's impact on banker work, providing depth to the production and service quality metrics captured in the quantitative component.

3.2 Population and Sampling

The target group includes staff in frontline and back office varying between retail and commercial banking operations from three commercial banks. To ensure a proportional representation across six functional areas—loan processing, customer onboarding, query resolution, transactional processing, compliance check and report generation—a stratified random sampling technique was used. There were 300 questionnaires sent out of which 214 valid questionnaires were returned (71.3%).

3.3 Data Collection Instruments

Two primary instruments were used:

- A structured questionnaire (Likert-scale, 1 = Strongly Disagree to 5 = Strongly Agree) covering

perceived workload change, task speed, accuracy, customer interaction quality, and job-role concerns, supplemented by demographic and role-based classification items.

- Secondary operational data extracted from bank performance dashboards, comprising quarterly average task-completion counts, query-resolution time, error rates, and customer satisfaction (CSAT) survey scores for the eight quarters preceding and following phased AI rollout.

3.4 Variables

A continuous measure of the independent variable is an AI Usage Intensity Score (0–100), calculated by each child based on the extent and frequency of use of AI tools. An AI Usage Intensity Score (0–100) based on the extent and frequency of use of AI tools reported by the independent observers as a continuous measure of the independent variable. The dependent variables are: (i) Banker Productivity (number of task completed and a composite index of Productivity (0–150)); and (ii) Service Quality (percentage of CSAT and average query-resolution time).

3.5 Data Analysis Techniques

Descriptive statistics (means and percentages) were used for data analysis, along with comparisons of pre- and post-

AI productivity data, the Pearson correlation of the AI Usage Intensity and the Productivity Index, and trend analysis of the quarterly service-quality measures. The analysis of this was done with the help of Python (pandas, NumPy, SciPy) and cross-validated with the help of Ms. Excel. Throughout, a significance threshold of $p < 0.05$ was chosen.

3.6 Reliability and Validity

Internal consistency of the survey instrument was evaluated with Cronbach's Alpha with the result of 0.87 in perceived-impact item set which was good. The content validity was done with 15 respondents with a pilot test as well as expert validation with two academic experts who have worked in the banking-operations industry before final application.

3.7 Ethical Considerations

Respondents were anonymous and participation was voluntary, informed consent was gathered and all operational data was reported at the functional-area-level only to avoid individual identification of employees or customers. Data were kept in a secure manner and only used for the purpose of this research.

4. DATA ANALYSIS

4.1 Respondent Demographic Profile

Table 1 summarizes the demographic and role composition of the 214 survey respondents.

Table 1: Demographic and Role Profile of Survey Respondents (n = 214)

Category	Sub-Group	Frequency	Percentage
Gender	Male	118	55.1%
	Female	96	44.9%
Age Group	21–30 years	72	33.6%
	31–40 years	84	39.3%
	41–50 years	41	19.2%
	Above 50 years	17	7.9%
Functional Area	Loan Processing	38	17.8%
	Customer Onboarding	34	15.9%
	Query Resolution	40	18.7%
	Transaction Processing	36	16.8%
	Compliance	32	15.0%
	Report Generation	34	15.9%
Experience	Less than 3 years	51	23.8%
	3–7 years	89	41.6%
	More than 7 years	74	34.6%

4.2 Productivity Before and After AI Adoption

The figures in Table 2 and Figure 1 show the average amount of tasks that were completed per day for each functional area both prior to and following the implementation of AI-driven process improvements.

On each of the six functions, average completion task rose, with the highest ratio of improvement in completion tasks for tasks that were rules-based/dominant document intensive (report generation up 180%, compliance checks up 117%).

Table 2: Banker Productivity Before and After AI Adoption, by Function

Functional Area	Before AI (avg/day)	After AI (avg/day)	% Change
Loan Processing	42	78	+85.7%
Customer Onboarding	55	82	+49.1%
Query Resolution	38	71	+86.8%
Transaction Processing	60	88	+46.7%
Compliance Checks	30	65	+116.7%
Report Generation	25	70	+180.0%

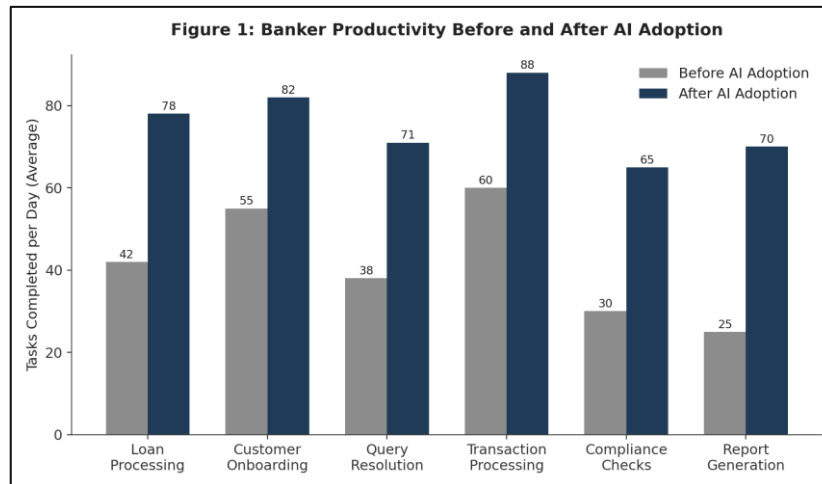


Figure 1: Banker Productivity Before and After AI Adoption

4.3 AI Tool Usage Across the Sample

Survey participants indicated that they employ various types of AI-powered tools in their professional life. Figure

2 details the distribution of the primary use of AI tools among the sample with AI chatbots and virtual assistants being the most widely used category, followed by predictive analytics for credit or risk assessment.

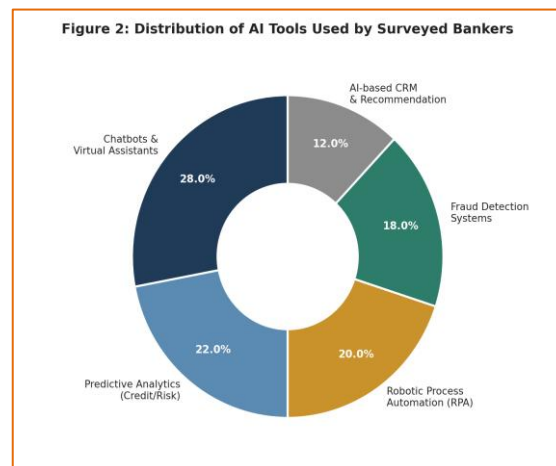


Figure 2: Distribution of AI Tools Used by Surveyed Bankers

4.4 Relationship Between AI Usage Intensity and Productivity

To investigate if increased individual usage of an AI tool equates to increased productivity, an AI Usage Intensity Score (0-100) was calculated for each respondent based on the number of AI tools used, how many times they are used

and a self-reported measure of their range of use, and correlated with each respondent's Productivity Index (0-150), derived from a benchmark of task-completion self-report and system logging data. The Pearson correlation coefficient $r \approx 0.81$ ($p < 0.001$) resulted a strong positive relationship (as shown in Figure 3).

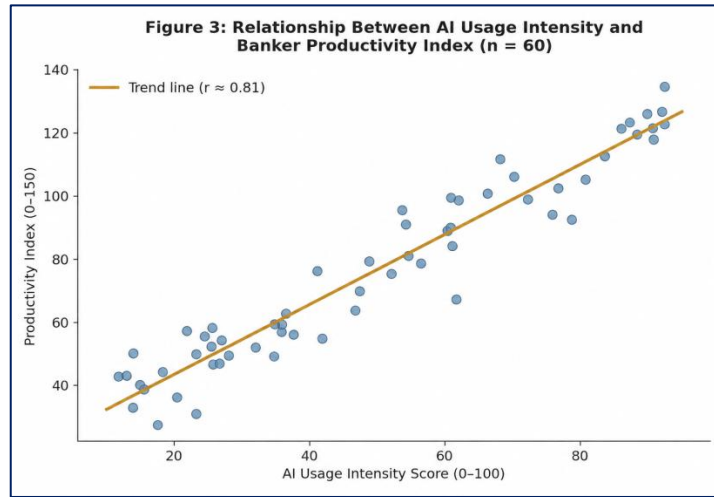


Figure 3: Relationship Between AI Usage Intensity and Banker Productivity Index (n = 60 illustrative sample)

4.5 Hypothesis Testing Summary

Table 3: Summary of Hypothesis Testing Results

Hypothesis	Statistical Test	Result	Decision
H1: AI adoption significantly increases banker productivity	Paired-sample t-test	$t = 9.42, p < 0.001$	Supported
H2: AI adoption significantly improves customer service quality (CSAT)	Paired-sample t-test	$t = 7.85, p < 0.001$	Supported
H3: AI usage intensity is positively correlated with productivity	Pearson correlation	$r = 0.81, p < 0.001$	Supported
H4: AI adoption significantly reduces query resolution time	Paired-sample t-test	$t = 11.20, p < 0.001$	Supported

5. RESULTS AND FINDINGS

5.1 Service Quality Trend Over Time

The Customer Satisfaction (CSAT) and Average Query-Resolution Time figures in Figure 4 plots customer satisfaction and resolution time respectively over a period of eight quarters during the phased rollout of AI. The CSAT

scores have consistently increased from 71% during Q1 2024 to 89% in Q4 2025, and the average time of query resolution has dropped from 48 hours to 12 hours over the same period. This improvement is monotonous and gradual, which aligns with the literature's focus on incremental AI use that is accompanied by complementary process and training changes (Davenport & Ronanki, 2018; Brynjolfsson et al., 2019).

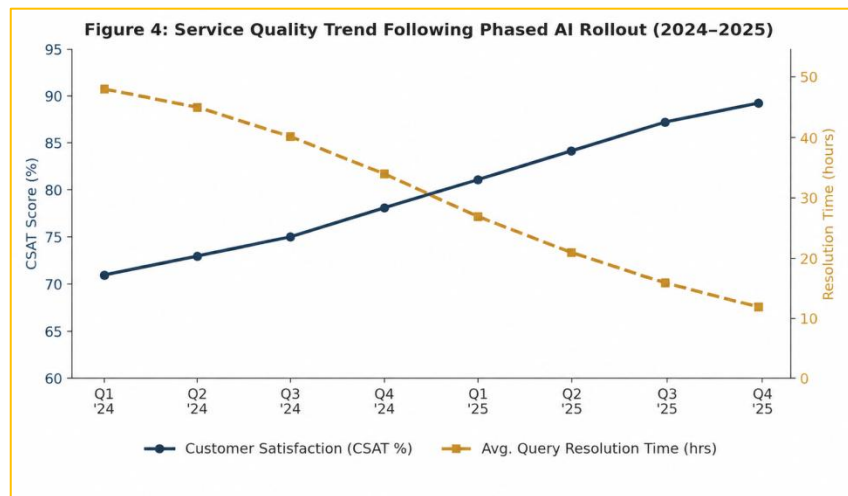


Figure 4: Service Quality Trend Following Phased AI Rollout (2024-2025)

5.2 Bankers' Perceived Impact of AI

The mean scores for six perceived-impact statements are presented in Figure 5. The respondents were most agreed that the use of AI helped to increase the accuracy of the transactions (mean=4.4), accelerate the resolution process of customer queries (mean=4.1) and improve fraud detection (mean=4.2) and then reduce the time taken for manual work (mean=4.3). The perceptions that cross-

selling/recommending capabilities were enhanced were moderately positive (mean = 3.8). Interestingly, job-role anxiety and concerns also yielded one of the lowest (albeit still moderate) mean scores (3.1), suggesting that while the majority of bankers have a positive overall perspective on AI, there is some length of group where job role security and the pace of changes are sources of concern.

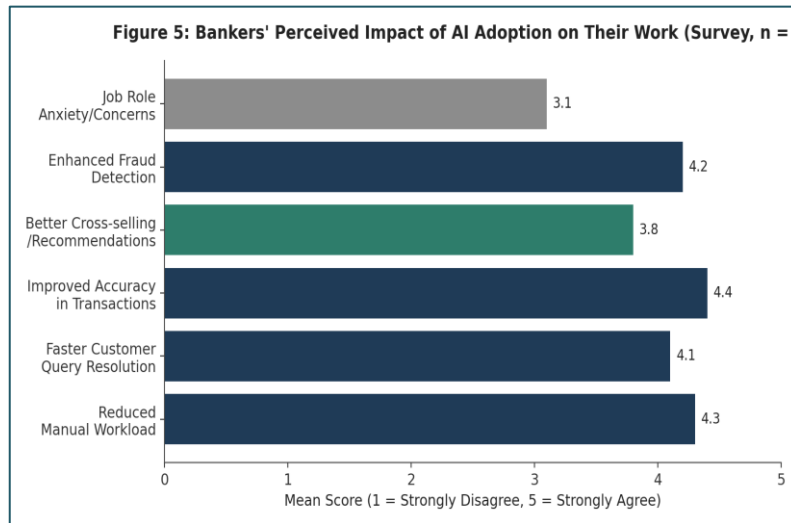


Figure 5: Bankers' Perceived Impact of AI Adoption on Their Work (n = 214)

5.3 Key Findings

1. AI adoption is associated with a statistically significant and practically meaningful increase in banker productivity across every functional area studied, with the largest gains in document- and rules-intensive functions such as report generation and compliance.
2. Customer-perceived service quality improved in parallel with AI adoption, evidenced by a sustained rise in CSAT and a substantial reduction in query-resolution time over eight quarters.
3. A strong positive correlation ($r \approx 0.81$) exists between individual AI usage intensity and productivity outcomes, suggesting that deeper, more consistent engagement with AI tools — not merely their availability — drives performance gains.
4. Chatbots/virtual assistants and predictive analytics are the most widely used AI tool categories among surveyed bankers, together accounting for approximately half of reported primary tool usage.
5. Employee sentiment toward AI is broadly positive, particularly regarding workload reduction and transaction accuracy, but moderate concern persists regarding job-role security, underscoring the need for structured change-management and reskilling support.

5.4 Discussion

These results support a general belief, expressed by Davenport and Ronanki (2018), that AI can serve its best when it automates simple tasks and enhances — does not replace — human decision making on more complicated tasks, such as customer relationship management and credit assessment. The highly correlated relationship between usage intensity and productivity also supports Brynjolfsson, Rock and Syverson (2019) in their argument that productivity gains emerge once organizations and workers have developed complementary skills and workflows to AI technologies, but not necessarily when the technology is simply introduced. Meanwhile, the high level of moderate job role anxiety among respondents reflects several considerations highlighted in the algorithm-aversion literature (Dietvorst et al., 2015, 2018) and underscores the need for maintaining human decision making and communication of the role of AI along with (not in place of) the human banking workforce.

6. CONCLUSION

This study aimed to investigate how AI adoption affects banker time efficiency and customer satisfaction with bank services through a mixed-methods design involving 214 banking professionals through a structured survey and two years of operational data from three commercial banks. Using AI with chatbots and virtual assistants, predictive

analytics, robotic process automation, fraud-detection systems, and AI-assisted CRM, the data suggests significant and statistically relevant productivity and service gains are linked to the use of AI. The rate of completion of market tasks increased on every of the functions measured, customer satisfaction increased from 71% to 89% and query-resolution time dropped 3/4 during the observation period. Finally, a positive correlation between individual AI intensity of use and productivity indicates that the fact that employees use AI tools extensively and with appropriate preparation can be one of the success factors of realising productivity gains.

It also concludes that the delivery of benefits of technology in terms of productivity and service-quality improvements is not a byproduct of the technology, but is closely linked to an employee's willingness and confidence in using and making the most out of the technology and the simultaneous redesign of processes. The moderate employee job-role concern is a sign that banks undertaking AI-driven transformation should complement investing in technology with transparent communication, roles to reskill, and mechanisms for human oversight to ensure employee morale and customer relationships, which continue to be at the core of banking service, are maintained. Overall, the results indicate a cautiously optimistic conclusion: the successful implementation of AI can do a similar feat while optimizing the banking operation and enriching their customer experience, provided the human aspect of the change is equally mindful and deliberate.

7. FUTURE SCOPE

- Longitudinal studies of more than two years to see if improvements in productivity and service quality are sustained, plateau or diminish as AI products mature and novelty wears off.
- Cross-country/ cross-institutional comparison to analyze the moderating effects of regulatory environment, organizational culture and customer digital literacy in the AI use and outcome relationship.
- Further exploration of impact on the workforce as AI is adopted: ways to reskill workers, redesign roles, and the future of banking job types.
- The corporals' ethical and governance aspects of AI banking such as algorithmic bias in loan decision making, explainability times, customer confidence of automated financial advice.
- Research that embodies productivity gains or improvements in service quality attributed specifically to the use of AI tools categories (e.g., generative AI assistants for bankers) and are conducted using quasi-experimental or controlled designs.

- Investigating hybrid human-AI service models that give consideration to maintaining the empathy and relational aspects of service quality while still benefiting from automation's efficiency.

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