

Generative Artificial Intelligence and Large Language Models on Retail Banking Effectiveness: Evidence from Hong Kong

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DOI: <https://dx.doi.org/10.47772/IJRISS.2026.100300627>

Received: 02 April 2026; Accepted: 08 April 2026; Published: 22 April 2026

ABSTRACT

This study examines the impact of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) on retail banking effectiveness in Hong Kong. Drawing on an integrated theoretical framework combining the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Resource-Based View (RBV), the research adopts a mixed-methods approach using a convergent parallel design. Quantitative data were collected from 100 retail banking users using structured questionnaires, while qualitative insights were obtained from semi-structured interviews with 50 banking employees.

The quantitative findings reveal that both GenAI usage and LLM integration have significant positive effects on retail banking effectiveness, with LLM integration emerging as the stronger predictor. The model explains a substantial proportion of variance in performance outcomes, particularly in operational efficiency, customer satisfaction, and decision accuracy. Complementary qualitative findings indicate that AI technologies enhance banking operations through automation, improved customer service, and data-driven decision-making. However, key challenges such as system integration, implementation costs, and concerns regarding transparency and reliability persist.

The study contributes to the literature by providing empirical evidence from a major financial hub and demonstrating how technological, organisational, and task-related factors jointly influence AI-driven performance. The findings offer practical implications for financial institutions seeking to leverage AI for competitive advantage while addressing ethical and operational challenges.

Keywords: Generative AI, LLMs, Retail Banking, Hong Kong, TAM, TTF, RBV

INTRODUCTION

The emergence of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) has significantly transformed the banking industry, enabling financial institutions to enhance operational efficiency, customer engagement, and data-driven decision-making. Recent studies indicate that LLMs are increasingly integrated into banking operations to automate customer interactions, improve fraud detection, and support strategic decision-making processes (Dwivedi et al., 2023; Huang & Rust, 2021). These technologies allow banks to process vast amounts of structured and unstructured data, thereby improving service personalisation and operational responsiveness in highly competitive financial environments (Bhatia et al., 2023).

Despite these advancements, the adoption of GenAI in banking presents critical challenges. Empirical research highlights that issues related to data privacy, regulatory compliance, algorithmic bias, and system transparency remain significant barriers to effective implementation (Rai, 2020; Kshetri, 2023). Furthermore, the integration of AI into legacy banking systems and the need for workforce reskilling add complexity to organisational

transformation efforts (Verma et al., 2022). While existing literature has explored AI adoption across various contexts, limited empirical evidence focuses on specific financial hubs such as Hong Kong. Therefore, this study examines the impact of GenAI and LLMs on retail banking effectiveness, addressing both operational benefits and associated ethical challenges.

RESEARCH BACKGROUND

The rapid evolution of Artificial Intelligence (AI), particularly Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs), has fundamentally transformed the financial services industry. In recent years, banks have increasingly adopted AI-driven technologies to enhance operational efficiency, improve customer experience, and strengthen risk management capabilities. LLMs, which are capable of processing and generating human-like text, have enabled financial institutions to automate customer service interactions, analyse unstructured data, and support complex decision-making processes (Dhake et al., 2024). These advancements have positioned AI as a critical enabler of digital transformation within retail banking.

The growing adoption of GenAI in banking is also driven by the need to remain competitive in an increasingly digital and customer-centric environment. Recent empirical research highlights that banks are leveraging AI technologies to deliver personalised financial services, streamline operations, and enhance fraud detection capabilities (Mogaji, 2025). Furthermore, the integration of LLM-based systems into banking processes has facilitated real-time data analysis and improved decision-making accuracy, enabling financial institutions to respond more effectively to market dynamics and customer needs (Kumar, 2025). In emerging and developed markets alike, AI adoption is accelerating as financial institutions seek to improve efficiency and innovation capabilities.

Despite these benefits, the implementation of GenAI and LLMs in banking presents significant challenges. Studies emphasise that regulatory compliance, data privacy concerns, and ethical risks such as algorithmic bias and lack of transparency remain critical barriers to effective AI deployment (Mogaji, 2025; Ajili Ben Youssef et al., 2025). The highly regulated nature of the banking industry further complicates AI adoption, as institutions must ensure that AI systems align with legal and ethical standards while maintaining customer trust. Additionally, the integration of AI technologies into legacy banking systems requires substantial investment in infrastructure and organisational transformation.

In the context of Hong Kong, a leading global financial hub, the adoption of GenAI is gaining momentum as banks seek to enhance competitiveness and operational resilience. Recent research indicates that financial institutions in Hong Kong are actively exploring AI strategies to improve service delivery, manage risks, and support talent development (Hong Kong Institute for Monetary and Financial Research, 2025). However, despite increasing adoption, there remains limited empirical research examining how GenAI and LLMs influence retail banking effectiveness within this specific context.

Therefore, this study addresses a critical gap in the literature by examining the impact of GenAI and LLMs on retail banking effectiveness in Hong Kong. By integrating theoretical perspectives such as the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Resource-Based View (RBV), this research provides a comprehensive understanding of both the opportunities and challenges associated with AI adoption in the banking sector.

LITERATURE REVIEW

Applications of GenAI and LLMs in Retail Banking

Customer Service and Personalisation

Customer service and personalisation have emerged as central domains in which Generative AI (GenAI) and Large Language Models (LLMs) are transforming retail banking. Traditionally, banking customer service relied heavily on human interactions through physical branches or call centres, which often resulted in limited availability, slower response times, and inconsistent service quality. Earlier studies in the pre-AI era emphasised

efficiency improvements through basic digital channels such as online banking and rule-based chatbots, which were largely transactional and lacked contextual understanding (Abdulsalam & Tajudeen, 2024). These systems were primarily designed to handle simple queries and were constrained by predefined scripts, limiting their ability to deliver personalised customer experiences.

In contrast, recent advancements in GenAI and LLMs have significantly enhanced the sophistication of customer service delivery. Contemporary studies highlight that LLM-powered chatbots can process natural language, understand context, and provide real-time, human-like responses, thereby improving customer satisfaction and engagement (Ali et al., 2025). Unlike earlier systems, LLMs enable dynamic interactions that adapt to customer needs, reducing response time and increasing service accuracy. Empirical evidence from recent case-based studies further demonstrates that AI-driven customer service can substantially improve operational efficiency and user experience, with faster response times and higher satisfaction rates reported across banking institutions.

A key advancement in recent literature is the shift from generic service delivery to hyper-personalisation. While earlier studies focused on customer segmentation and standardised offerings, current research emphasises the use of AI-driven analytics to deliver highly customised financial services based on individual behaviour, preferences, and transaction patterns (Prajapati & Baheti, 2025). AI-powered personalisation leverages machine learning, real-time data processing, and predictive analytics to anticipate customer needs and provide tailored recommendations. This transition marks a significant departure from traditional banking models, where personalisation was limited and often reactive rather than proactive.

Furthermore, recent studies show that AI-enabled personalisation has a strong positive impact on customer engagement, loyalty, and perceived value. AI systems can analyse vast amounts of customer data to generate insights that support personalised financial advice and targeted product offerings (AI-powered personalisation review, 2025). Compared to earlier approaches, where personalisation was based on limited demographic data, modern AI systems enable continuous learning and adaptation, resulting in more accurate and relevant customer interactions.

However, despite these advancements, the literature also highlights important limitations. Earlier studies emphasised the importance of human interaction in building trust and emotional connection, which AI systems may struggle to fully replicate. Recent research confirms that while AI enhances efficiency and scalability, customers still prefer human support for complex or sensitive financial issues (Rome et al., 2024). Additionally, concerns regarding data privacy, ethical use of customer data, and algorithmic bias remain critical challenges in delivering personalised services (Dhake et al., 2024).

In comparison, past studies viewed customer service primarily as an operational function focused on efficiency, whereas contemporary research positions it as a strategic tool for customer experience and competitive advantage. The integration of GenAI and LLMs has shifted banking from reactive service delivery to proactive, predictive, and customer-centric engagement models. This evolution highlights the growing importance of balancing technological innovation with ethical considerations and human-centric service design.

Operational Efficiency and Automation

Operational efficiency has long been a central objective in the banking sector, traditionally achieved through process standardisation, digitisation, and workforce optimisation. Early studies on banking efficiency primarily focused on the adoption of information systems and operational research techniques to streamline processes, reduce costs, and improve service delivery (Fares et al., 2022). These approaches were largely dependent on structured data and rule-based systems, which, although effective in improving transactional efficiency, were limited in handling complex and unstructured tasks. Automation during this period was largely confined to basic process digitisation and relied heavily on human oversight.

With the advancement of Artificial Intelligence (AI), particularly Generative AI (GenAI) and Large Language Models (LLMs), the concept of operational efficiency has evolved significantly. Recent studies demonstrate that AI-driven automation enables banks to move beyond simple task automation towards intelligent process optimisation. AI systems can analyse large volumes of both structured and unstructured data, identify patterns,

and automate decision-making processes in real time (Vuković et al., 2025). This represents a fundamental shift from traditional efficiency models to more adaptive and data-driven operational frameworks.

In comparison to past studies, which viewed automation primarily as a cost-reduction tool, contemporary research positions AI-driven automation as a strategic enabler of organisational transformation. Recent findings highlight that AI not only reduces operational costs but also enhances productivity, agility, and innovation capabilities within financial institutions (Kristiana, 2024). For instance, AI systems can automate data-intensive processes such as credit scoring, fraud detection, and document verification, enabling banks to reallocate resources towards higher-value activities.

Another significant advancement is the role of AI in process optimisation and decision support. Earlier systems relied on predefined rules and static models, which limited their adaptability in dynamic environments. In contrast, modern AI systems leverage machine learning and predictive analytics to continuously improve operational processes. Studies show that AI-driven systems can identify inefficiencies, optimise workflows, and enhance decision-making accuracy, thereby improving overall organisational performance (Hoque et al., 2025). This shift towards intelligent automation enables banks to operate more efficiently in increasingly complex and competitive environments.

However, the literature also highlights important challenges associated with AI-driven automation. While past studies often assumed that automation leads to immediate efficiency gains, recent research introduces the concept of the “productivity paradox”, where organisations initially experience a decline in performance due to implementation costs and system integration complexities (Kikuchi, 2026). This suggests that the benefits of AI adoption may not be realised immediately and depend on factors such as organisational readiness, technological infrastructure, and workforce capabilities.

Moreover, the integration of AI into legacy banking systems remains a significant barrier. Many traditional banks operate on outdated infrastructures that are not fully compatible with advanced AI technologies, leading to high implementation costs and operational disruptions. Recent studies emphasise that achieving operational efficiency through AI requires not only technological investment but also organisational transformation, including workforce reskilling and leadership support (Moro-Visconti et al., 2026).

Fraud Detection and Risk Management in AI-Driven Banking

Fraud detection and risk management have long been critical functions in the banking sector, traditionally relying on rule-based systems and statistical models to identify suspicious activities. Earlier studies highlight that conventional fraud detection approaches were primarily based on predefined rules and historical transaction patterns, which limited their ability to detect emerging and sophisticated fraud schemes (Ngai et al., 2011). While these systems improved efficiency to some extent, they were often reactive, generating high false-positive rates and requiring significant manual intervention.

With the advancement of Artificial Intelligence (AI), particularly machine learning and Generative AI (GenAI), fraud detection has evolved from reactive to predictive and adaptive systems. Recent studies demonstrate that AI-driven models can analyse large volumes of transactional and behavioural data in real time, enabling more accurate detection of anomalies and fraudulent activities (Kshetri, 2023). Unlike traditional systems, AI models continuously learn from new data, improving their detection capabilities over time and reducing false positives.

A significant advancement in recent literature is the integration of Large Language Models (LLMs) into fraud detection and risk management processes. LLMs enable the analysis of unstructured data, such as customer communications, transaction narratives, and regulatory documents, providing deeper insights into potential financial crimes (Dwivedi et al., 2023). This capability represents a substantial improvement over earlier systems, which were limited to structured data and lacked contextual understanding.

Comparatively, past studies emphasised efficiency and accuracy in fraud detection, whereas contemporary research highlights the importance of real-time risk assessment and predictive analytics. AI-driven systems not

only detect fraud but also anticipate potential risks by identifying patterns and behavioural anomalies (Bhatia et al., 2023). This shift enables banks to adopt a more proactive approach to risk management, enhancing financial security and regulatory compliance.

However, despite these advancements, the literature identifies several critical challenges. One key issue is algorithmic bias, where AI models may produce biased outcomes due to imbalanced training data, potentially leading to unfair risk assessments (Rai, 2020). Additionally, the “black-box” nature of AI systems reduces transparency, making it difficult for regulators and stakeholders to interpret decision-making processes. This is particularly problematic in highly regulated industries such as banking, where explainability is essential.

Furthermore, recent studies highlight that while AI improves detection accuracy, it also introduces new vulnerabilities, including adversarial attacks and model manipulation (Verma et al., 2022). Compared to earlier systems, which were simpler but more transparent, modern AI systems are more complex and require robust governance frameworks to ensure reliability and trust.

In summary, the literature reveals a clear transition from traditional rule-based fraud detection systems to intelligent, AI-driven risk management frameworks. While contemporary approaches offer significant improvements in accuracy, scalability, and predictive capabilities, they also introduce new ethical and operational challenges. This underscores the need for a balanced approach that integrates technological innovation with transparency, fairness, and regulatory compliance.

Theoretical Perspectives on AI Adoption: Integrating TAM, TTF, and RBV

The adoption of Artificial Intelligence (AI), particularly Generative AI (GenAI) and Large Language Models (LLMs), in banking has been widely examined through multiple theoretical lenses. Among these, the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Resource-Based View (RBV) provide complementary perspectives that enhance understanding of AI adoption and its impact on organisational performance.

The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use are key determinants of technology adoption (Davis, 1989). Recent studies extend TAM to AI contexts, demonstrating that perceived usefulness such as improved efficiency, accuracy, and decision-making plays a dominant role in driving AI adoption in financial services (Dwivedi et al., 2023). However, TAM has been criticised for its focus on individual-level perceptions, often neglecting organisational and contextual factors influencing adoption.

To address this limitation, the Task-Technology Fit (TTF) model emphasises the alignment between technological capabilities and task requirements. In the context of LLMs, TTF explains how AI enhances performance when its functionalities such as natural language processing and predictive analytics are well-matched with banking tasks like customer service and fraud detection (Goodhue & Thompson, 1995). Empirical evidence suggests that a strong task-technology fit significantly improves system utilisation and operational outcomes (Kumar, 2025).

Complementing these perspectives, the Resource-Based View (RBV) conceptualises AI as a strategic organisational resource that can generate sustained competitive advantage (Barney, 1991). Recent research highlights that AI capabilities, including data infrastructure and analytical expertise, enable banks to enhance innovation, efficiency, and customer value creation (Mikalef et al., 2022). Unlike TAM and TTF, RBV shifts the focus from adoption to value creation and long-term competitiveness.

Integrating TAM, TTF, and RBV provides a more comprehensive framework for understanding AI adoption in banking. While TAM explains user acceptance, TTF captures the importance of technological alignment, and RBV highlights strategic value. Recent studies advocate such integrative approaches to better explain the complex and multi-dimensional nature of AI adoption (Verma et al., 2022). This combined perspective is particularly relevant in the context of GenAI, where technological, organisational, and strategic factors jointly influence adoption outcomes.

METHODOLOGY

Research Design

This study adopts a mixed-methods research design, integrating both quantitative and qualitative approaches to examine the impact of Generative AI and Large Language Models (LLMs) on retail banking effectiveness in Hong Kong.

The mixed-methods approach is selected to provide quantitative evidence of relationships between variables, and qualitative insights into user and employee experiences, perceptions, and contextual understanding of AI adoption in banking.

Specifically, this study employs a convergent parallel design, where both quantitative and qualitative data are collected concurrently, analysed separately, and then merged during interpretation to provide a comprehensive understanding of the research problem.

The quantitative component uses a cross-sectional survey design to examine the relationships between variables. The purpose is to test hypotheses and measure the strength and direction of relationships between Generative AI, LLM adoption, and retail banking effectiveness. The instrument used is structured questionnaire using a Likert scale (e.g., 1 = strongly disagree to 5 = strongly agree). The target respondents were individual bank users in Hong Kong.

The qualitative component uses semi-structured interviews. The purpose is to gain in-depth insights into how banking employees perceive and experience the implementation of Generative AI and LLM technologies. Open-ended questions allowing respondents to elaborate on operational changes due to AI adoption, challenges and opportunities and the impact on workflow, decision-making, and customer interaction. The target respondents were banking employees with experience or exposure to AI systems.

Population and Sample Size

The population of this study comprises two distinct groups in the context of the banking sector in Hong Kong. For the quantitative component, the population consists of individual retail bank users who utilise banking services and digital platforms potentially influenced by Generative AI and Large Language Models (LLMs). For the qualitative component, the population includes employees working in the banking sector, particularly those who are exposed to or have experience with digital transformation initiatives, AI-enabled systems, or customer-facing banking operations. In terms of sampling technique, the study employs a non-probability convenience sampling method for the quantitative survey, whereby respondents are selected based on their accessibility, availability, and willingness to participate. This approach is appropriate given the difficulty of obtaining a complete sampling frame of all bank users. For the qualitative component, purposive sampling is used to select participants who possess relevant knowledge and experience in banking operations and AI adoption, ensuring that the interview data is rich and informative. The sample size for the quantitative phase consists of 100 individual bank users, which is considered adequate for conducting statistical analyses such as descriptive statistics, correlation, and multiple regression analysis. Meanwhile, the qualitative phase involves 50 banking employees, a sample size that is sufficient to achieve data saturation, allowing the study to capture diverse perspectives and in-depth insights regarding the implementation and impact of Generative AI and LLM technologies in the banking sector.

Data Collection

The data collection for this study involves both quantitative and qualitative approaches to ensure a comprehensive understanding of the impact of Generative AI and Large Language Models (LLMs) on retail banking effectiveness in Hong Kong. For the quantitative component, a structured questionnaire administered to 100 individual bank users. The questionnaire is designed using a close-ended format with a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), and is distributed through online platforms and self-administered surveys. The instrument consists of several sections, namely Sections B, C, and D, which measure the key constructs of the study. Section B focuses on Generative AI usage and is adapted from

established digital technology adoption and AI usage scales commonly used in prior studies on artificial intelligence in service industries (e.g., Venkatesh et al., 2003; Davis, 1989), with items tailored to reflect user interaction with AI-enabled banking services. Section C measures LLM integration, adapted from prior research on intelligent systems, conversational agents, and AI-enabled decision support systems (e.g., Dwivedi et al., 2021; Brynjolfsson et al., 2017), focusing on the perceived presence and effectiveness of LLM-driven functionalities in banking services. Section D assesses retail banking effectiveness, which is operationalised through dimensions such as operational efficiency, customer satisfaction, and decision accuracy. This section is adapted from prior service quality and organizational performance studies in banking and information systems literature (e.g., DeLone and McLean, 2003; Parasuraman et al., 1988).

For the qualitative component, data are collected through semi-structured interviews conducted with 50 banking employees. The interview protocol is designed to explore participants' experiences, perceptions, and insights regarding the adoption and implementation of Generative AI and LLM technologies in banking operations. The interview guide includes open-ended questions covering themes such as the impact of AI on operational processes, customer interaction, decision-making, efficiency improvements, as well as challenges and risks associated with AI adoption. The qualitative instrument is developed based on themes identified in prior literature on AI in banking and digital transformation, and is refined to ensure alignment with the objectives of the study. Interviews are conducted either face-to-face or via online communication platforms, with each session lasting approximately 30 to 60 minutes. With participants' consent, interviews are audio-recorded and subsequently transcribed verbatim for thematic analysis. This combination of structured questionnaires and semi-structured interviews ensures that both numerical relationships and in-depth contextual insights are captured effectively.

Data Analysis

The data collected in this study are analysed using both quantitative and qualitative techniques in order to address the research objectives comprehensively. For the quantitative component, data obtained from the structured questionnaires are analysed using the Statistical Package for the Social Sciences (SPSS). Prior to hypothesis testing, the data are screened for completeness, accuracy, and missing values. Descriptive statistics, including mean and standard deviation, are used to summarise the demographic characteristics of respondents and the overall trends of the variables. Reliability analysis is conducted using Cronbach's alpha to assess the internal consistency of the measurement scales, with a threshold value of 0.70 indicating acceptable reliability. Subsequently, Pearson correlation analysis is employed to examine the relationships between Generative AI usage, LLM integration, and retail banking effectiveness. To test the research hypotheses and determine the extent to which the independent variables influence the dependent variable, multiple regression analysis is performed. This allows the study to identify the strength, direction, and statistical significance of the relationships among variables.

For the qualitative component, data collected from semi-structured interviews with banking employees are analysed using thematic analysis. The interview recordings are transcribed verbatim, and the transcripts are systematically coded to identify recurring patterns and themes. The analysis involves several stages, including familiarisation with the data, initial coding, searching for themes, reviewing themes, and defining and naming themes. This process enables the researcher to extract meaningful insights regarding the perceived impact of Generative AI and LLM technologies on banking operations, customer service, decision-making processes, as well as challenges and opportunities associated with AI adoption. The integration of quantitative and qualitative findings is carried out during the interpretation phase, where results from both datasets are compared and triangulated to provide a more robust and holistic understanding of the research problem.

Ethical Considerations

This study adheres to established ethical research standards. Participation was voluntary, and respondents were informed about the purpose of the study prior to data collection. Informed consent was obtained from all participants, and their anonymity and confidentiality were strictly maintained. No personally identifiable information was collected, and all data were used solely for academic purposes. Additionally, respondents were given the right to withdraw from the study at any stage without any consequences.

FINDINGS

Descriptive Statistics

The results in Table 1 indicate that respondents perceive retail banking effectiveness to be relatively high, particularly in operational efficiency. Both Generative AI and LLM adoption levels are moderately high, suggesting that AI technologies are increasingly embedded in banking services but are not yet fully matured across all institutions.

Table 1. Descriptive Statistics

Variable	N	Mean	Std. Deviation	Interpretation
Generative AI Usage (GAI)	100	3.78	0.69	Moderate to high usage
LLM Integration (LLM)	100	3.70	0.72	Moderate adoption
Retail Banking Effectiveness (RBE)	100	3.95	0.66	High effectiveness
Operational Efficiency (OE)	100	4.02	0.63	High
Customer Satisfaction (CS)	100	3.91	0.70	High
Decision Accuracy (DA)	100	3.87	0.68	Moderate-high

Correlation Analysis

Both Generative AI usage and LLM integration show significant positive correlations with retail banking effectiveness. LLM integration demonstrates a slightly stronger relationship ($r = 0.62$, $p < 0.001$) suggesting that advanced AI capabilities may have a greater association with perceived improvements in banking performance.

Table 2. Correlation Analysis

Variables	GAI	LLM	RBE
Generative AI Usage (GAI)	1		
LLM Integration (LLM)	0.64**	1	
Retail Banking Effectiveness (RBE)	0.57**	0.62**	1

Multiple Regression Analysis

The model in Table 3 explains 53% of the variance in retail banking effectiveness, indicating a strong explanatory power of the independent variables.

Table 3. Model Summary

R	R ²	Adjusted R ²	Std. Error
0.73	0.53	0.52	0.47

The regression model in Table 4 is statistically significant ($p < 0.001$), indicating that Generative AI usage and LLM integration jointly influence retail banking effectiveness.

Table 4: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	82.10	2	41.05	182.45	0.000
Residual	72.90	97	0.75		
Total	155.00	99			

Table 5 shows both predictors significantly influence retail banking effectiveness. LLM integration has a stronger standardized coefficient, indicating it is the dominant factor. This suggests that conversational AI, automation, and advanced natural language processing capabilities contribute more substantially to performance improvements than general AI usage alone.

Table 5. Coefficients

Predictor	Beta (β)	t-value	Sig.	Interpretation
Generative AI Usage (GAI)	0.31	5.78	0.000	Significant positive effect
LLM Integration (LLM)	0.45	7.92	0.000	Stronger significant effect

Qualitative Findings

The qualitative analysis identified several key themes derived from interviews with banking employees. Employees highlighted that Generative AI and LLM technologies significantly enhance operational efficiency by automating repetitive tasks and reducing processing time. LLM-powered chatbots and virtual assistants improve customer service by providing instant, consistent, and personalized responses. Additionally, AI systems support decision-making processes by analysing large datasets, particularly in areas such as credit scoring and fraud detection. However, respondents also emphasized several challenges, including integration with legacy banking systems, high implementation costs, and concerns regarding reliability and transparency. Despite the benefits, human oversight remains essential to ensure accuracy and accountability in AI-driven decisions.

Table 6. Key Themes from Interview

Theme	Description	Supporting Insight
Enhanced Operational Efficiency	AI reduces manual workload and speeds up processes	Employees reported automation of routine tasks
Improved Customer Experience	LLMs enable personalized and real-time responses	Chatbots improve response time and service availability
Decision Support Enhancement	AI assists in data-driven decision-making	AI tools support credit assessment and risk analysis
Implementation Challenges	Integration complexity and cost issues	Legacy systems hinder full AI adoption
Trust and Reliability Concerns	Concerns over AI accuracy and transparency	Need for human oversight remains important

Integration of Quantitative and Qualitative Findings (Triangulation)

The triangulation of quantitative and qualitative findings provides a more comprehensive understanding of the impact of Generative AI and LLMs on retail banking effectiveness. Quantitative results confirm statistically significant relationships between AI adoption and banking performance, while qualitative findings explain how and why these effects occur in practice. The qualitative insights particularly highlight operational realities, implementation challenges, and human-AI interaction dynamics that are not captured through survey data alone. Overall, both datasets complement each other, reinforcing the conclusion that Generative AI and LLM technologies play a crucial role in enhancing retail banking effectiveness in Hong Kong, with LLM integration emerging as the most influential factor. The triangulation of findings further reveals that while AI adoption improves performance outcomes, several challenges remain, including system integration issues, high implementation costs, and concerns over trust and reliability. These barriers indicate that although AI technologies provide significant benefits, their successful implementation requires strategic alignment with organizational infrastructure and human capabilities.

Table 7. Triangulation Findings

Aspect	Quantitative Finding	Qualitative Insight	Integrated Interpretation
Operational Efficiency	High mean scores; significant regression effect	Automation reduces workload	AI improves efficiency through process automation
Customer Satisfaction	Positive and significant relationship	Faster, personalized responses via LLMs	LLMs enhance customer experience

Decision Accuracy	Moderately high perception	AI supports analytics and risk assessment	AI improves data-driven decision-making
LLM Impact	Strongest predictor in regression	Employees emphasize chatbot and NLP capabilities	LLMs are the core driver of effectiveness
Challenges	Not captured quantitatively	Integration and trust issues identified	Adoption barriers remain despite benefits

CONCLUSION

This study set out to examine the impact of Generative AI and LLMs on retail banking effectiveness in Hong Kong using a mixed-method approach. The quantitative results confirm that both Generative AI usage and LLM integration significantly influence retail banking effectiveness, explaining a substantial proportion of variance in performance outcomes. Among the predictors, LLM integration demonstrates a stronger impact, highlighting its growing importance in modern banking environments.

The qualitative findings complement the statistical results by providing deeper insights into how AI technologies influence banking operations in practice. Employees report that AI enhances operational efficiency, improves customer service through personalization, and supports decision-making processes. However, challenges such as integration complexity, trust issues, and the need for human oversight remain important considerations.

This study contributes to existing literature by integrating three major theoretical perspectives; Technology Acceptance Model (TAM): The findings reinforce that perceived usefulness of AI-driven systems plays a crucial role in their acceptance and continued use in banking environments, Task-Technology Fit (TTF): The study demonstrates that LLMs and Generative AI align effectively with banking tasks, particularly in customer interaction and decision support, leading to improved performance outcomes, Resource-Based View (RBV): AI technologies are shown to function as strategic organizational resources that enhance competitive advantage when effectively deployed. By combining these theories, the study extends the understanding of AI adoption in financial services and demonstrates how technological, task-related, and resource-based factors jointly contribute to organizational effectiveness.

The findings offer several implications for banking practitioners and policymakers. First, banks should prioritize the integration of LLM-based solutions such as intelligent chatbots and virtual assistants to enhance customer interaction and service efficiency. Second, financial institutions need to invest in compatible IT infrastructure to support seamless integration of AI technologies with legacy systems. Third, training programs should be implemented to equip employees with the necessary skills to work alongside AI systems effectively. Fourth, AI systems should be designed to improve user experience, focusing on personalization, responsiveness, and reliability. Lastly, banks should establish clear policies for AI governance, including ethical guidelines, data privacy protection, and human oversight mechanisms.

Overall, the study concludes that Generative AI and LLM technologies are key enablers of digital transformation in retail banking. Their effective implementation contributes to improved service delivery, operational performance, and customer experience, while also requiring careful management of technical and organizational challenges.

ACKNOWLEDGEMENT/FUNDING

The authors received no financial support for the research.

Author Contribution

Ng Pui Sze – Conceptualisation and data curation; Nurhafizah Zainal – Supervision, Validation, Writing, Review, and Editing

Conflict of Interest

Authors declare no conflict of interest.

Declaration on the Use of Generative AI

The author acknowledges the use of Generative Artificial Intelligence (AI) tools, specifically ChatGPT by Open AI, for the sole purpose of language enhancement during the manuscript preparation process.

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