Artificial Intelligence Applications and the Impact on Banking Operations

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Artificial Intelligence (AI) has emerged as a powerful force in the banking and financial sectors, reshaping traditional processes and unlocking new opportunities for efficiency and inclusion. However, its adoption is not without challenges, particularly concerning ethical risks, regulatory compliance, and operational limitations. The purpose of this paper is to explore AI in banking applications and its impact on banking operations. First, a literature review examines the multifaceted role of AI in banking, exploring its applications, the ethical risks it poses, and the strategies required to ensure equitable and responsible deployment. Second, we study 39 banks and their AI applications. Third, based on our research, we develop and distribute opinion surveys to students. The survey results show that students believe most jobs eliminated due to AI will be in the lower levels of financial organizations, particularly bank tellers. While AI offers substantial benefits, its success relies on robust governance frameworks, transparent systems, and ongoing efforts to mitigate bias.

Keywords: artificial intelligence, fintech, AI in banking

INTRODUCTION

Artificial Intelligence (AI) has rapidly transformed the financial industry, offering unprecedented opportunities to enhance efficiency, decision-making, and customer experience. From automating lending processes to enabling real-time fraud detection, AI systems are revolutionizing traditional practices. However, these innovations are accompanied by significant ethical and operational challenges, particularly regarding bias, transparency, and regulatory compliance. This literature review examines the multifaceted role of AI in banking, exploring its applications, the ethical risks it poses, and the strategies required to ensure equitable and responsible deployment. By synthesizing insights from diverse sectors and regulatory perspectives, this paper highlights both the potential and limitations of AI-driven financial technologies.

The purpose of this paper is to explore applications of AI in banking, its impact on operations, and potential limitations. First, a literature review examines the multifaceted role of AI in banking, exploring its applications, the ethical risks it poses, and the strategies required to ensure equitable and responsible deployment. Second, we study 39 banks and their AI applications. Third, based on the study, we developed a survey questionnaire. The questionnaires were sent to students for their opinion and received 109 responses. We will analyze the results and discuss the implications at the end of this paper.

LITERATURE REVIEW

AI Applications in Banking

Artificial intelligence (AI) technologies have significantly improved the lending process by enhancing efficiency, accuracy, and fairness. AI-driven tools for income verification and credit scoring reduce biases often present in human decision-making. According to Howe (2023), automated systems streamline income assessments, ensuring accuracy by evaluating diverse data sources, such as pay stubs and bank statements, in real-time. These systems have been especially impactful for underserved populations, such as low-income and thin-file borrowers, by reducing barriers to credit access.

Moreover, Tigges et al. (2024) explore the integration of alternative data, such as utility payments and digital footprints, to create more holistic credit profiles. This approach reduces default rates and provides lenders with a comprehensive view of borrower behavior, thereby fostering financial inclusion. However, they caution that the use of unconventional data must be carefully managed to avoid privacy violations and unintended biases.

AI in Risk Assessment and Financial Inclusion

AI's capacity to analyze vast amounts of data has revolutionized risk assessment in financial institutions. Perry and Martin (2023) highlight how AI enhances predictive models by integrating non-traditional data sources, thereby enabling lenders to better evaluate creditworthiness for historically excluded groups. For example, AI-powered tools in the mortgage market have expanded homeownership opportunities by addressing systemic biases in property valuations and loan approvals.

Despite these advancements, the potential for AI systems to perpetuate biases inherent in training datasets remains a challenge. Perry and Martin (2023) argue that implementing "algorithmic reparation," or designing AI models that actively counteract historical disadvantages, is essential to achieving equitable outcomes. These findings underscore the dual role of AI in enhancing financial inclusion while necessitating robust governance mechanisms to mitigate risks.

Ethical Risks and Bias in AI-Driven Financial Decision-Making

AI models, while powerful, are prone to embedding and amplifying societal biases present in their training data. Garcia et al. (2024) identify key sources of algorithmic bias in credit decisions, including data imbalances and proxies that inadvertently correlate with sensitive attributes such as race or gender. These biases manifest as disparate impacts, where ostensibly neutral policies disproportionately disadvantage marginalized groups.

Similarly, Broussard (2023) highlights the role of systemic inequalities in shaping AI systems. She notes that biased algorithms often emerge when developers prioritize accuracy over fairness, thereby neglecting the diverse experiences of underrepresented populations. Addressing these challenges requires integrating anti-bias frameworks into AI development processes, such as the use of demographic parity and equalized odds metrics.

Real-world examples highlight the consequences of algorithmic bias in financial decision-making. Kelley et al. (2022) examine how excluding sensitive attributes, like gender, from Machine Learning (ML) models can paradoxically increase gender discrimination due to the reliance on proxy variables. They advocate for incorporating controlled demographic data to identify and mitigate biases effectively.

Crosman (2022) offers a contrasting perspective, highlighting how some fintech companies have successfully reduced biases through regular fairness testing and second-level reviews of declined applications. For instance, tools like FairPlay identify missed opportunities for minority borrowers, demonstrating that deliberate bias-mitigation strategies can lead to more equitable outcomes without compromising profitability.

Fair Lending and Regulatory Compliance

The implementation of fair lending laws, such as the Equal Credit Opportunity Act (ECOA) and the Fair Housing Act (FHA), is central to promoting equity in AI-driven financial systems. Flo (2022) emphasizes that financial institutions must perform disparate impact testing to identify and address biases in lending outcomes. The three-part test—evaluating outcomes for protected groups, business justification, and less discriminatory alternatives—is a cornerstone of compliance.

AI offers unique opportunities to enhance compliance efforts. For example, Brotcke (2022) highlights the use of advanced fairness metrics, such as SHAP and LIME, to interpret complex ML models and ensure adherence to fair lending principles. These tools help institutions identify variables that disproportionately affect protected classes, enabling proactive adjustments to lending algorithms.

Barr (2023) underscores the importance of transparency and accountability in AI systems, particularly in ensuring fair outcomes for marginalized communities. He warns of risks such as digital redlining and reverse redlining, where algorithms exclude or exploit nonwhite borrowers. To address these risks, regulators are revising the Community Reinvestment Act (CRA) to include more granular assessments of retail lending practices and community development activities.

Additionally, Barr highlights initiatives to improve collateral valuation processes, such as reconsiderations of value in home appraisals, to address systemic biases in wealth-building opportunities. These measures align with broader efforts to integrate fair lending principles into AI governance frameworks, advancing a more equitable financial system.

Fraud Detection and Cybercrime Prevention

AL-Dosari et al. (2024) found that banking institutions in Qatar use AI to combat advanced threats from cybercriminals. Anand et al. (2022) mentioned the potential for utilizing machine learning methods to predict loan defaults. Advances in ML can be credited for many of the improvements in AI technologies, including improvement of risk management and fraud management processes (Boukherouaa et al., 2021). Farayola (2024) suggested that a combination of blockchain, business intelligence, and AI could be the key to mitigating cyber threats to the financial ecosystem. Johora et al. (2024) has similar viewpoints for enhancing fraud detection using a combination of AI techniques.

Risk Management in Financial AI Applications

AI-driven risk management systems are transforming financial institutions by improving predictive accuracy and operational efficiency. Natarajan et al. (2024) highlight how machine learning (ML) models, such as XGBoost and neural networks, outperform traditional methods in identifying credit risk and fraud. However, these systems also introduce unique challenges, including data quality issues, lack of transparency, and susceptibility to novel threats.

Thomas (2024) critiques the limitations of AI in fraud detection, noting its inability to decode highly complex, unstructured data or detect sophisticated fraudulent schemes, such as those in the Wirecard scandal (BBC News, June 25, 2020). He emphasizes the importance of combining AI tools with human oversight to effectively address these gaps.

Brotcke (2022) explores tools like SHAP and LIME, which enhance transparency and fairness by revealing how AI models make decisions. Young (2024) underscores the importance of unified data platforms in wealth management, which reduce fragmentation and improve the accuracy of AI-generated insights. These approaches highlight the necessity of designing AI systems that prioritize fairness while maintaining operational effectiveness.

Regulatory Perspectives on AI and Ethical AI Development

Global regulatory efforts are focusing on managing the risks and opportunities associated with AI in finance. The European Union's AI Act categorizes applications by risk, banning certain uses while imposing strict requirements on high-risk systems (The Economist, 2024). Similarly, Barr (2023) advocates for increased transparency and accountability in AI systems to prevent discriminatory practices, such as digital redlining.

India's efforts to become a "fintech nation" include initiatives such as Project Utkarsh 2.0, which aims to align fintech regulations with global standards and address emerging challenges in AI and decentralized finance (Economic Times, 2024). These initiatives strike a balance between fostering innovation and ensuring consumer protection.

Implementing ethical AI standards is fraught with difficulties, including a lack of clear guidelines and the high costs of compliance. Crosman (2022) highlights the importance of industry-led solutions, such as fairness testing and second-level reviews, to bridge these gaps. Moreover, Thomas (2024) advocates for a collaborative approach involving policymakers, developers, and ethicists to create frameworks that promote transparency, accountability, and safety.

Synthesis of Literature Review

The literature highlights AI's transformative potential in financial services, particularly in lending, credit scoring, and risk management. However, it also underscores significant ethical and operational challenges, including bias, transparency, and regulatory compliance. Insights from non-banking sectors, such as insurance and wealth management, demonstrate the broader applicability of AI. For instance, Max Life Insurance's use of AI in underwriting and fraud detection complements lessons from banking, emphasizing the importance of data quality and human oversight (Team, 2024).

Future research should explore advanced methodologies for bias detection and mitigation, the role of AI in decentralized finance, and global approaches to regulating emerging technologies. Furthermore, interdisciplinary studies on the societal impacts of AI could provide valuable insights for developing ethical frameworks.

EXPERIMENT DESIGN AND RESEARCH METHODS

Research Questions

After the literature review, the following questions are raised:

1. What banking operations have the potential to benefit from using AI technology?
2. What is (are) the job(s) affected most by AI in banking operations?
3. Whether ethical concerns are associated with the use of AI in banking operations or not? What is the most pressing ethical concern about AI in banking operations?
4. What is the difference of perceptions among 1) Computer Information Systems students, 2) Finance students, and 3) other students regarding the use of AI in banking and ethical concerns?
5. What is the difference in perceptions between 1) graduate students and 2) undergraduate students about the use of AI in banking and ethical concerns?

Cross-institutional Competitive Study

A total of 39 local and foreign banks were initially examined in this study for their applications of artificial intelligence. Appendix 1 lists these banks and their respective AI applications. Generative AI and predictive analysis appear to be the most popular AI tools. Among the banks reviewed, 25 are based in the U.S. and 14 are from other countries.

Questionnaire and Survey

Based on the study of 39 banks, we developed a survey questionnaire (See Appendix 2) and distributed it electronically to students in various CIS and Finance classes via Google Forms.

Research Questions and Hypotheses

We use descriptive statistics to answer the questions 1, 2, and 3 from survey. To answer question 4, the following hypotheses were set:

H₀: *There is no difference in the perceptions of students among IS, Finance and other majors about ethical concern of AI* (H_0: $\mu_{is} = \mu_f = \mu_o$).

Ha: *There is a difference in the perceptions of students among IS, Finance, and other majors about ethical concern of AI.*

To answer question 5, the following hypotheses were set:

H₀: *There is no difference in the perceptions of students between graduate and undergraduate about ethical concern of AI* (H_0: $\mu_g = \mu_u$).

Ha: *There is a difference in the perceptions of students between graduate and undergraduate about ethical concern of AI* (H_0: $\mu_g \neq \mu_u$).

109 students from various Computer Information Systems and Finance classes (graduate/undergraduate classes in Enterprise Resources Planning, Web Applications Development, and Data Warehouses, Financial Modeling, Fixed Income, Corporate Finance, etc.) participated in the survey.

SURVEY RESULTS

Figure 1 shows the reported majors of survey respondents. Of the students surveyed, 45.9% were Finance majors followed by 28.4% that were Computer Information Systems majors. The remaining 25.7% of respondents came from other departments within the College of Business.

FIGURE 1
MAJOR OF SURVEY RESPONDENTS

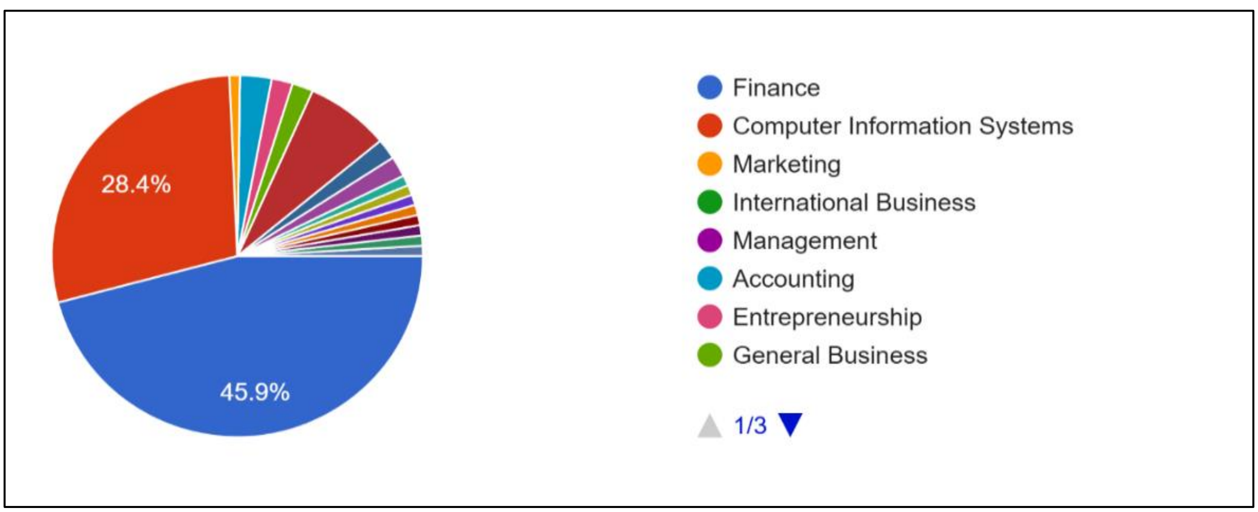


Figure 2 displays the status of student respondents. Of the students surveyed, 59.6% were undergraduate students and 40.4% were graduate students.

FIGURE 2
STATUS OF STUDENT RESPONDENTS

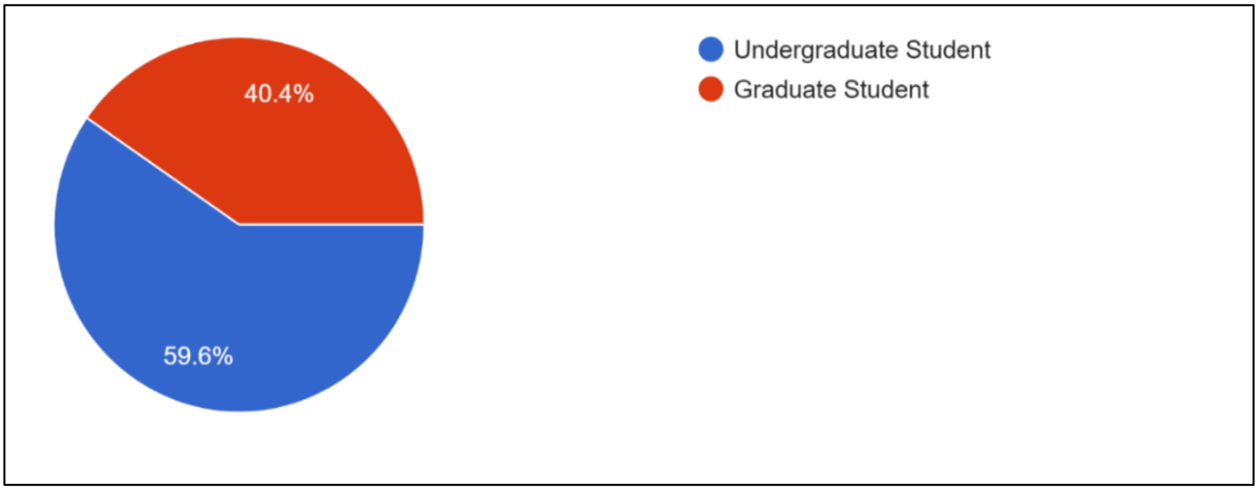


Figure 3 displays student responses to the question, "What banking operations have the potential to benefit from using AI technology?" Students could select multiple options or provide additional answers. The most frequently selected answers were fraud detection (87.2%), improved chatbots (85.3%), and better predictive analytics (78.9%).

FIGURE 3
PERCEIVED BENEFITS OF AI IN BANKING

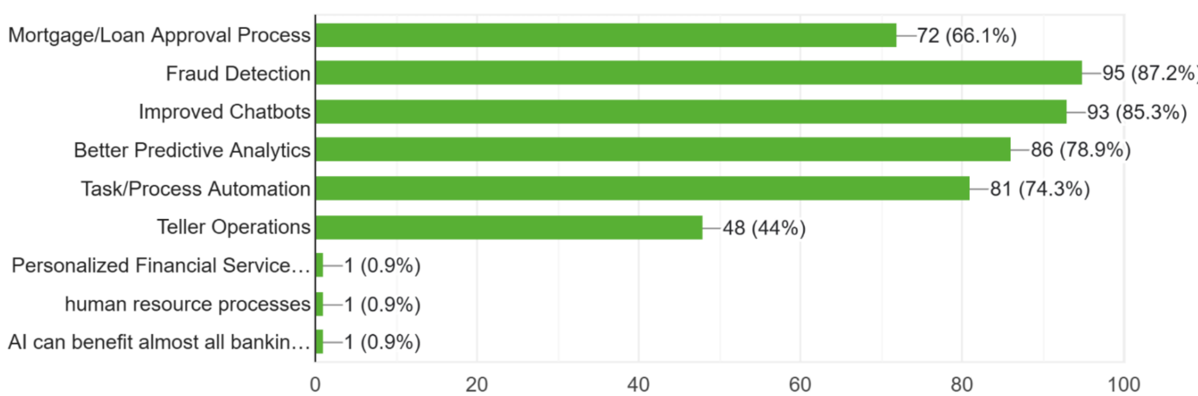


Figure 4 displays how students ranked each banking function in terms of the potential benefits it could gain from the implementation of AI technologies. Students ranked each function from 1 to 5, with 1 denoting the least benefit and 5 denoting the most benefit. As shown in Figure 4, the functions that received the most rankings of 5 were improved chatbots, fraud detection, and better predictive analytics.

FIGURE 4
BENEFIT RANKINGS

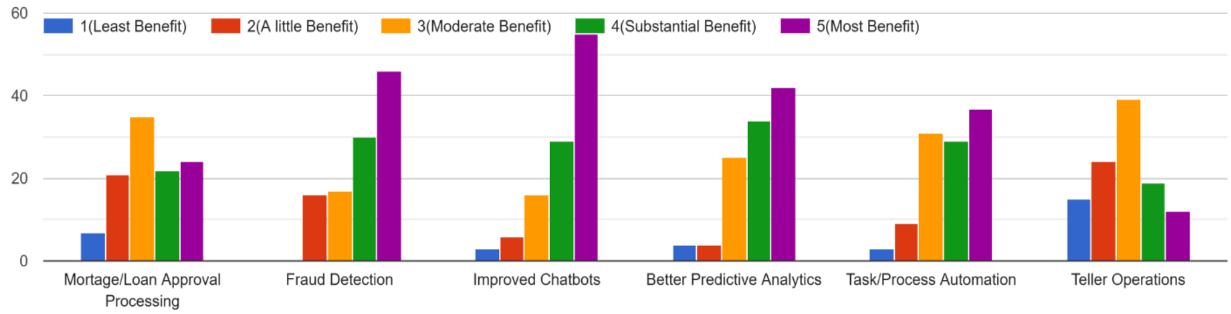


Figure 5 shows the survey responses to the question "What job(s) will be replaced by AI technologies?" The most common answers were Bank Tellers, which 61.5% of students selected, and Mortgage/Loan Officers, which 27.5% of students selected.

FIGURE 5
AT-RISK JOBS

Figure 6 shows the survey responses to the question, "What ethical concerns are associated with the use of AI in banking operations?" Students could select multiple answers. The most common responses were that jobs will be replaced by AI technologies (83.5%) and concerns about consumer data privacy (76.1%).

FIGURE 6
ETHICAL CONCERNS IN AI

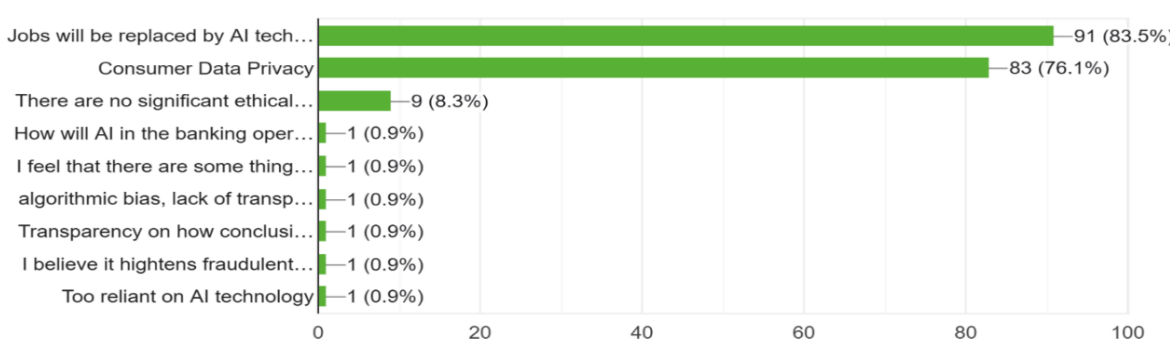
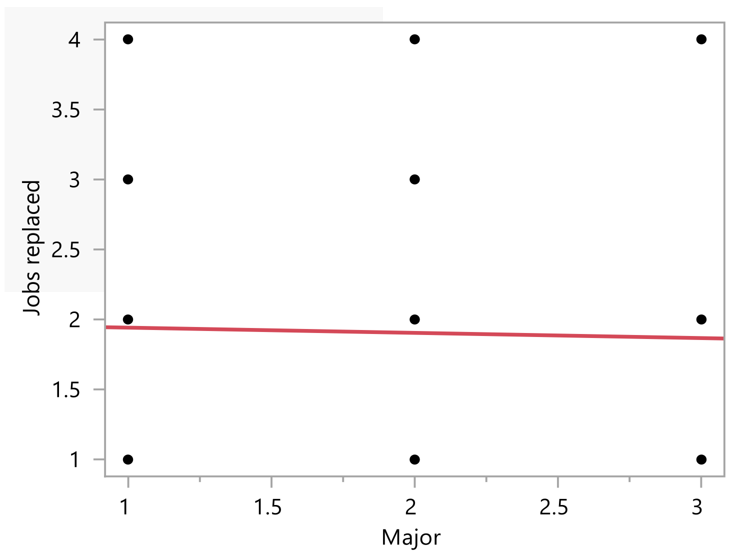


Figure 7. shows the ANOVA analysis of ethical concern by student major to answer the research question “What is the difference of perceptions among 1) Computer Information Systems students, 2) Finance students, and 3) other business students regarding the use of AI in banking and ethical concerns?”

There is no significant difference among IS, Finance, and other majors regarding their ethical concerns about AI at a 5% significant level. This suggests that, regardless of their educational background, students’ views on the potential problems of AI are similar. This may be because the application of AI is still in its early stages, and many students may not have had the opportunity to use AI in banking applications.

FIGURE 7
ANOVA ANALYSIS OF ETHICAL CONCERN BY MAJORS

a) Bivariate Fit of Ethical Concern by Majors



b) Summary Statistics

	Value	Lower 95%	Upper 95%	Signif. Prob
Correlation	-0.2952	-0.45788	-0.11339	0.0018*
Covariance	-0.12368			
Count	109			

Variable	Mean	Std Dev
Graduate or not	0.40367	0.492899
Ethical Concerns	2.394495	0.850036

Linear Fit

Ethical Concerns = 2.6 - 0.5090909*Graduate or not

Summary of Fit

RSquare	0.087143
RSquare Adj	0.078611
Root Mean Square Error	0.815941
Mean of Response	2.394495
Observations (or Sum Wgts)	109

c) Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	6.800334	6.80033	10.2144
Error	107	71.236364	0.66576	**Prob > F**
C. Total	108	78.036697		0.0018*

Parameter Estimates

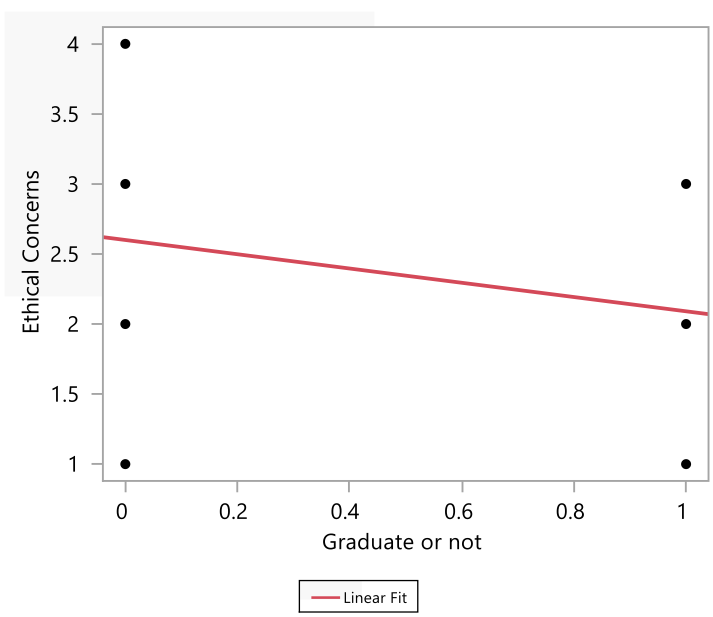
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	2.6	0.101205	25.69	<.0001*
Graduate or not	-0.509091	0.15929	-3.20	0.0018*

Figure 8 shows data to address the research question "What is the difference of perceptions among 1) graduate students and 2) undergraduate students on the use of AI in banking and ethical concerns?"

The simple linear regression indicates a significant difference in the perceptions of students between graduate and undergraduate levels regarding the ethical concerns of AI. Graduate students are inclined to choose one of the concerns instead of both. Undergraduate students are more likely to choose both as ethical concerns. One thing to note is almost all graduate students are from the Computer Information System discipline. Other interesting ethical concerns are algorithmic bias and transparency on how AI models make conclusions. Given the current development of AI technology, it is worth considering.

FIGURE 8
LINEAR REGRESSION OF ETHICAL CONCERN BY DEGREE (GRADUATE VS UNDERGRADUATE)

a) Bivariate Fit of Ethical Concerns by Graduate or not



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SUMMARY OF FINDINGS AND CONCLUSIONS

In conclusion, AI has emerged as a powerful force in the banking and financial sectors, reshaping traditional processes and unlocking new opportunities for efficiency and inclusion. However, its adoption is not without challenges, particularly concerning ethical risks, regulatory compliance, and operational limitations. This review demonstrates that while AI offers substantial benefits, its success relies on robust governance frameworks, transparent systems, and ongoing efforts to mitigate bias. By drawing on insights from diverse applications and sectors, the financial industry can harness AI's potential responsibly, fostering a more equitable and innovative future.

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APPENDIX 1: FINANCIAL INSTITUTIONS IN THIS STUDY

Bank	AI tools	Applications	Country
JPMorgan Chase	LLM Suite, AI-powered fraud detection systems.	Customer service enhancement, fraud detection, operational efficiency.	US
Morgan Stanley	AI@Morgan Stanley Debrief, AI knowledge assistant.	Summarizing meetings, drafting follow-up emails, information retrieval for financial advisors.	US
Bank of America	AI assistant for client meeting preparation.	Enhancing efficiency in preparing for client meetings.	US
Goldman Sachs	Generative AI tools for developers.	Improving productivity and maintaining robust data strategies.	US
Citigroup	Comprehensive AI strategy implementation.	Enhancing various banking operations through a four-phase AI strategy.	US
Visa	Over 500 generative AI applications.	Enhancing productivity, countering sophisticated fraud methods, improving employee efficiency, protecting consumers from fraud, and driving innovation.	US
HSBC	AI-powered fraud detection tools.	Detecting payment fraud, protecting consumer data.	United Kingdom
ANZ	Centralized data and analytics unit focusing on AI adoption.	Streamlining operations, enhancing data analytics, improving responsiveness to customers and stakeholders.	Australia
Deutsche Bank	AI-powered fraud detection systems, client advisory tools.	Fraud detection, personalized client advisory services.	Germany
Wells Fargo	Predictive analytics, chatbots.	Customer service, loan approvals.	US
Royal Bank of Canada	AI for personalized banking services.	Customer engagement, risk management.	Canada
Barclays	Fraud detection, virtual assistants.	Transaction security, customer support.	United Kingdom

Santander	AI in risk management (Kairos).	Risk assessment, personalized marketing.	Spain
BBVA	AI chatbots, fraud detection algorithms.	Customer service, security.	Spain
Standard Chartered	NLP for compliance, chatbots for customer service.	Regulatory compliance, client support.	United Kingdom
HSBC	AI-Powered Anti-Money Laundering Tools, Chatbots	Fraud detection, customer support, and regulatory compliance.	United Kingdom
Wells Fargo	Predictive Analytics Tools, Digital Assistant (Erica)	Customer experience improvement, fraud prevention.	US
Deutsche Bank	Generative AI for trading, AI compliance tools	Automated trading insights, enhanced decision-making.	Germany
UBS	Advanced Risk Management Systems, NLP tools	Risk assessment, client service enhancement.	Switzerla nd
Royal Bank of Canada (RBC)	AI-Powered Investment Advisors, Client Analytics	Personalized financial advice, predictive client insights.	Canada
US Bank	Expense Wizard (artificial intelligence-based expense management mobile app inclusive of chatbot)	Business expense management, expense report generation	US
PNC	Claim Predictor, PINACLE mobile banking platform	Prevent lost revenue due to denied claims, cash forecasting	US
Bank of NY Mellon Corp	enterprise AI platform, Eliza	enhance client service, predictive analytics, automation, and anomaly detection	US
Ally Financial	mobile platform uses a machine-learning-based chatbot	assist customers with questions, transfers, and payments/provides payment summaries	US
Capital One	Eno virtual assistant	Eno VA: lets users text questions, receive fraud alerts, take care of tasks like paying credit cards, tracking account balances, viewing available credit & checking transactions	US
Discover	Google Cloud’s Vortex AI platform	contact center agents have access to: document summarization capabilities, real-time search assistance to help handle customers’ questions and issues	US
SoFi	Risk Data Platform Chatbot, Galileo Financial Technologies’ conversational artificial intelligence (AI) engine, Auto Invest feature	identifying, preventing, and mitigating fraud to safeguard the company’s assets and customer data; conversational AI engine: common inquiries including customer onboarding & support; automatically invest client money into a diversified portfolio	US
TD Bank	Layer 6 machine learning models	mortgage pre-approvals, term life insurance application approvals	US

USAA Federal Savings Bank	Machine learning algorithms, natural language processing, chatbots, Robotic Process Automation (RPA)	analyzing customer data for targeted product offers, help customers with online chats, predict customer needs	US
Commonwealth Bank of Australia (CommBank/CBA)	GenAI	scam loss prevention, fraud prevention, faster loan decisions, identifying unused benefits	Australia
ScotiaBank	AI based chatbot, LLMs	answer customer questions, rapid data summarization, managing data assets	Canada
Key Bank	RPA	predictive analytics, detecting money laundering, investment research, mortgage processing	US
Fifth Third Bank	Genie chatbot, Optical Character Recognition (OCR), LLMs	processing document, streamlining customer requests/questions	US
M & T Bank	NLP(chatbot), ML, RPA, predictive analytics	automating customer service, tailored product recommendations, fraud detection/risk management, faster loan processing, automate routine tasks, customer insights	US
Truist	ML, chatbot, predictive analytics	targeted marketing, fraud detection/prevention, assisting customers, credit risk assessment, customer retention, operational efficiency, market analytics	US
Comerica Bank	bots, voice AI	automating business/management tasks for employees and bank customers, faster customer query resolution	US
Chime	predictive analytics	customer personalization, marketing/customer acquisition	US
Huntington Bank	"Money Scout" Ai-driven savings tool, GenAI	automated savings, fraud prevention/detection	US
Citizens Financial Group	NLP/chatbots, GenAI	fraud detection, developing code, automating customer chats	US

APPENDIX 2: SURVEY QUESTIONNAIRE

AI in Banking Survey

The purpose of this survey is to study the perceived impact of Artificial Intelligence (AI) on banking operations. Please answer the following questions:

1. What is your major?
   A. Finance B. Accounting
   C. Computer Information Systems D. Entrepreneurship
   E. Business F. Marketing
   G. Management
   H. Business Administration/General Business
   I. Other (List: ___________________________________)

2. I am a _________________ student.
   A. undergraduate B. graduate

3. What banking operations have the potential to benefit from using AI technology? Please select all that apply.
4.

Banking Operations	Yes	Ranking
A. Mortgage/Loan Approval Process		
B. Fraud Detection		
C. Improved Chatbots		
D. Better Predictive Analytics		
E. Task/Process Automation		
F. Teller Operations		
G. Other (List: _______________________________________)		
H. Other (List:____)		

4. What job(s) will be replaced by AI technologies?
   A. Mortgage/Loan Officers B. Bank Tellers
   C. Bank Managers
   D. Other (List: ____)

5. What ethical concerns are associated with the use of AI in banking operations?
   A. Jobs will be replaced by AI technology.
   B. Consumer Data Privacy
   C. Other (List: ____)
   D. There are no significant ethical concerns associated with the use of AI in banking.