

# Assessing Skill Gaps in the Era of AI in the Banking Sector

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**Abstract** -"Assessing Skill Gaps in the Era of AI in the Banking Sector" explores the gaps in AI-related skills among bank employees. Through a survey conducted using convenience sampling, we discovered significant deficiencies in technical competencies, despite employees' eagerness to adopt AI technologies. These findings highlight an urgent need for targeted training and development programs to bridge these gaps. While convenience sampling provided valuable initial insights, it has its limitations and may not fully represent the broader banking workforce. Therefore, further research with more rigorous sampling techniques is recommended. To effectively address these skill gaps, we advocate for continuous education and upskilling initiatives. Collaboration between banks, educational institutions, and AI experts is crucial to create effective training programs. The successful integration of AI in banking depends on the workforce's ability to adapt and thrive in an AI-driven environment, making the assessment and mitigation of skill gaps essential for the industry's future success.

**Keywords:** skill gap, AI, banking, etc.,

## INTRODUCTION

The current scenario is all about the use of technologies, predominantly Artificial Intelligence (AI). It crucially impacts the global economy, dynamic business world and the over all environments. *Merriam Webster* defines AI as "branch of computer science dealing with the simulation of intelligent behavior in computers. The capability of a machine to imitate intelligent human behavior". AI plays a major role in banking sector by improving security, efficiency and customer experiences. It automates patterned tasks like data entry and fraud detection, reducing operational costs. As this technology strongly imitates human intelligence it reduces the need of physical bank employees making the work easier, on the other hand it decreases the job opportunities in the banking sector.

The impact of AI on human skills will probably depend on the specific tasks and skills being automated. Some tasks may be more liable to automations, and some depends on human skills such as critical thinking and problem solving, this may become more valuable as AI continues to advance. The OECD international conference of AI in work, innovation, productivity and skills, discussed the skills needed for the effective adoption of AI in organization, success factor and challenges in training managers, workers and opportunities for policy makers to help workers acquire the necessary skills.

The current study indicates various contributions and take aways. Initially it hunts through the prevailing development in research and applications that explore the impact of AI on professional competencies and work environments. Secondly it outlines approaches that can help organizations and employees navigate the challenges associated with the increasing emphasis on upskilling and reskilling.

The research also investigates the potential long-term effects of AI adoption on career paths within the banking industry. It considers how traditional banking roles might evolve or be replaced, and what new positions might emerge as AI becomes more deeply integrated into financial services. This includes an analysis of the potential for AI to create new specializations within banking, such as AI ethics officers, machine learning engineers for financial

systems, or AI-human collaboration specialists. Furthermore, it also examines the broader implications of AI-driven skill shifts in banking for economic policy and labor markets. It considers how changes in the banking sector might influence other industries, and what lessons can be drawn from the banking experience to help prepare other sectors for AI integration.

The research also addresses the crucial issue of ensuring equitable access to upskilling and reskilling opportunities within the banking sector. It explores strategies for preventing the widening of skill gaps that could lead to increased inequality among banking professionals. By providing a comprehensive analysis of skill gaps in the era of AI in banking, this study aims to offer valuable insights for bank executives, policymakers, educators, and banking professionals. It seeks to contribute to the development of proactive strategies for addressing the challenges and leveraging the opportunities presented by AI in the banking sector

#### I. OBJECTIVES OF THE STUDY

- Investigate the readiness of bank employees to update their skillsets in the era of AI, focusing on their willingness and ability to learn new technologies and improve data analysis proficiency.
- Identify specific skill gaps among bank employees, particularly in areas like adaptability to new technologies, proficiency in data analysis, and cybersecurity Practices.

#### STATEMENT OF THE PROBLEM

The emergence of artificial intelligence (AI) in the banking sector is transforming traditional workflows, leading to significant automation of routine tasks and the emergence of new roles that require advanced technological competencies. However, this rapid technological transformation poses a substantial challenge: the current workforce may lack the necessary skills to operate effectively in this new AI-driven environment. The problem is dual: identifying the critical skills required for the future and developing effective reskilling programs to provide employees with these skills. Additionally, resistance to change among employees, along with potential job displacement fears, inflame the issue. Without a strategic approach to workforce reskilling, banks risk falling behind in innovation, facing operational inefficiencies, and experiencing a decline in employee morale and productivity. Therefore, it is very important to explore and implement comprehensive reskilling strategies that not only focus on technical training but also promotes a culture of continuous learning and adaptability. This study seeks to identify effective reskilling strategies that will enable the banking sector to seamlessly integrate AI technologies, enhance employee capabilities, and maintain a competitive edge in the rapidly evolving financial landscape.

Author (Year)	Description	Findings	Key Takeaways
Salman Bahoot et al. (2024)	"Artificial Intelligence in Finance: A Comprehensive Review Through Bibliometric and Content Analysis" provides a thorough examination of AI's use in finance, highlighting rapid development and diverse applications over the past two decades.	Bibliometric and content analysis from 1992 to March 2021 reveals significant growth in AI-related financial research, particularly in predictive systems, classification, and big data analytics. Identifies ten main research	Future research should address the impact of disruptive AI technologies on finance.

		streams.	
Martin Leo et al. (2019)	"Machine Learning in Banking Risk Management: A Literature Review" analyzes machine learning applications in managing various banking risks.	Reviews literature on machine learning techniques in credit, market, operational, and liquidity risk management. Significant progress made, but many areas remain underexplored.	Potential of machine learning to transform risk management by enhancing predictive accuracy and addressing complex risk patterns.
Omara H. Farese et al. (2022)	"Utilization of Artificial Intelligence in the Banking Sector: A Systematic Literature Review" offers a comprehensive analysis of AI's application in banking.	Systematic review of 44 articles identifying three primary research areas: Strategy, Process, and Customer. Develops a framework bridging academic research and industry practice, emphasizing AI's role in improving customer journey processes and strategic decision-making.	AI's transformative impact on banking services. Suggests future research directions to enhance understanding and implementation.
Aggarwal	"A study of AI in banking system"	Financial institutions	AI signific

al, A. (20 22)	highlights AI as a disruptive technology enhancing efficiency, accuracy, and customer satisfaction.	leverage AI technologies like chatbots and machine learning for service delivery and insights into customer behavior. Challenges include data privacy, cybersecurity risks, and need for robust risk management frameworks.	antly impact s the bankin g sector; continu ed researc h and develo pment are essenti al.
Rez a Fari shy	"The Use of Artificial Intelligence in Banking Industry" provides an overview of AI transforming the banking sector through a Systematic Literature Review (SLR).	AI applications include credit rating models and bank failure predictions. Logistic regression models establish credit card eligibility with 80.43% accuracy, while ANNs predict bank failures with 75.7% precision and recall rate.	AI enhanc es efficien cy, precisi on, and decisio n-making in bankin g; further researc h needed to explore full potenti al.
Sanj eeth a, M. B. F. (20 20)	"Drivers of Artificial Intelligence in Banking Service Sectors" examines factors influencing AI adoption in banking.	Qualitative study with semi-structured interviews highlights AI's potential in enhancing banking operations and customer service. Identifies key	Import ance of AI in the digital transfo rmatio n of banks; strategi es suggest

		drivers (technological advancements, organizational readiness) and barriers (conservative structures, lack of skilled personnel).	ed for successful AI implementation
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Table I:

REVIEW OF LITERATURE

In the context of the research topic "Assessing Skill Gaps in the Era of AI in the Banking Sector," several critical research gaps need addressing. While AI's transformative potential in banking operations, risk management, and customer service is well-documented, there is insufficient focus on the specific skills required for effective AI integration. Existing literature highlights the benefits and challenges of AI adoption but often overlooks the detailed competencies needed for banking professionals to leverage AI technologies fully. There is a need for comprehensive studies identifying the essential technical and soft skills, such as data analysis proficiency, machine learning understanding, and adaptability to technological changes. Moreover, the impact of AI on traditional roles and the evolving nature of job functions in the banking sector remain underexplored. Research should also address how educational institutions and training programs can better prepare the workforce for these emerging demands. By filling these gaps, future studies can provide actionable insights to bridge the skill gaps, ensuring that banking professionals are well-equipped to navigate and thrive in the AI-driven landscape.

II. Research Methodology

:This research employs a mixed-method approach to investigate the impact of AI on the banking sector and the resulting skill development needs for employees. The study primarily focuses on identifying and analysing the skill gaps that have emerged due to the introduction of AI technologies in banking operations.

The methodology combines quantitative and qualitative data collection and analysis techniques to provide a comprehensive understanding of the research aims. Quantitative methods may include surveys or statistical analyses of industry data to measure the extent of AI adoption and its effects on employee roles and skills. This could help identify trends and patterns across the sector. Qualitative methods might involve interviews with banking professionals, AI experts, and HR managers to gain deeper insights into the challenges and opportunities presented by AI integration. These could explore employee experiences, training needs, and organizational strategies for addressing skill gaps.

By integrating both data types, the research aims to provide a nuanced view of AI's impact on banking skills. This approach allows for triangulation of findings, enhancing the validity and reliability of the results. The mixed-method design enables the study to not only quantify the skill gaps but also to understand the context and complexities surrounding AI adoption and its implications for workforce development in the banking sector.

A. Theoretical Background

The rapid integration of Artificial Intelligence (AI) in the banking sector has triggered a significant shift in the skills required for industry professionals. This transformation is rooted in several theoretical frameworks that help explain the interplay between technological advancement and workforce dynamics. The theory of skill-biased technological change posits that technological innovations tend to favor skilled workers, potentially widening the gap between high-skilled and low-skilled labor. In the context of banking, this theory suggests that AI adoption may disproportionately benefit employees with advanced technological skills. Complementing this, the task-based approach to labor markets, as proposed by Autor, Levy, and Murnane, provides a nuanced understanding of how AI

affects different job roles by automating routine tasks while potentially creating new roles that require human judgment and creativity. Human capital theory, pioneered by Becker, underscores the importance of continuous learning and skill development, particularly relevant in the rapidly evolving AI landscape. Organizational learning theories, including the dynamic capabilities framework and the concept of absorptive capacity, offer insights into how banking institutions can adapt to technological changes and foster the necessary skills among their workforces. The job polarization theory further illuminates the potential widening of skill gaps, suggesting that AI might lead to a hollowing out of middle-skill jobs while increasing demand for both high-skill and low-skill positions. Lastly, the routine-biased technological change hypothesis provides a lens through which to examine how AI specifically impacts jobs with high routine content, potentially reshaping the skill requirements across various banking roles. These theoretical underpinnings collectively form a robust framework for assessing and understanding skill gaps in the era of AI within the banking sector.

#### *B. Scope of the Study*

This study examines the AI technologies currently being implemented in the banking sector, including but not limited to machine learning, natural language processing, robotic process automation, and blockchain. It analyzes how these AI technologies are transforming various banking operations such as customer service, fraud detection, risk management, and compliance. Surveys and interviews with banking professionals will be conducted to assess their current skill levels and understanding of AI technologies, identifying specific skills and knowledge areas lacking among employees at different organizational levels. Collaborating with AI experts and industry leaders, the study will delineate the skill sets required for effectively working with AI technologies in the banking sector, focusing on both technical skills. It will review existing training and development programs to evaluate their effectiveness in bridging the identified skill gaps, identifying best practices and areas for improvement. The study will focus on major banking institutions in the Saravanampatti area of Coimbatore, considering variations in skill gaps based on demographic factors such as age, gender, and educational background of the banking workforce.

#### *C. Research Methodology*

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#### *D. Source of data*

The data for this study was collected from the active bank employees. Quantitative data was gathered through structured questionnaires distributed via Google Forms. Qualitative data will be obtained from informal interviews and interaction with the bank employees. This dual approach ensures a comprehensive and detailed understanding of the research objectives.

#### *E. Sample Size*

The study targets the following sample size for collection of data: Questionnaires: 75 bank employees were surveyed using the structured questionnaire. Informal interactions were made as and when it was required. This method was found one of the comfortable methods to gather and understand the happenings.

#### F. Sampling method

The sampling method used to collect data is a convenient sampling method. Convenience sampling (also known as availability sampling) is a specific type of nonprobability sampling method that relies on data collection from population members who are conveniently available to participate in study. Convenience sampling is a type of sampling where the first available primary data source will be used for the research without additional requirements. In other words, this sampling method involves getting participants wherever you can find them and typically wherever is convenient.

#### G. Area of the study

The area of the research study was performed within saravanampatti, Coimbatore.

#### H. Limitations of the study:

- \*The survey was limited to a particular location (saravanampatti) due to lack of time.
- \*We were not able to cover a lot of banks.
- \*There was limited availability of bank branches.
- \*Limited availability of survey members because the survey was taken during the bank working hours.

## VI. RESULTS AND DISCUSSIONS

### A. Chi – Square

Adaptability to Learning New Technologies and Proficiency in Data Analysis

#### Hypothesis

- *Null Hypothesis ( $H_0$ ):* There is no significant association between age group and adaptability to learning new technologies.
- *Null Hypothesis ( $H_0$ ):* There is no significant association between years of experience and proficiency in data analysis.

*Null Hypothesis ( $H_0$ ):* There is no significant association between age and proficiency in data analysis.

Table II: Adaptability to Learning New Technologies and Proficiency in Data Analysis

Table III: Area of Improvement and Demographic Variables

Vari able	Chi- Squa re Valu e	Df	P- value	Signifi cance	Interpretatio n
Age Grou p	25.3 47	16	0.062	Not Signifi cant	No significant association between age group and perceived area of improvement.
Posit ion	22.7 86	16	0.119	Not Signifi cant	No significant association between position and perceived area of improvement.
Expe rienc e	30.4 56	16	0.015	Signifi cant	Significant association between



					experience and perceived area of improvement.
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Factor	Chi-Square Statistic	DF	P-value	Significance	Remark
Age Group and Adaptability to Learning New Technologies	16.59	16	0.413	Not Significant	Accept
Years of Experience and Proficiency in Data Analysis	7.65	16	0.959	Not Significant	Accept
Age and Proficiency in Data Analysis	2.34	16	0.99997	Not Significant	Accept

#### B. Kruskal-Wallis H test

##### *Soft Skills Are Essential for Adapting To AI Technologies In Banking*

The Kruskal-Wallis H test is a non-parametric statistical test used to determine if there are statistically significant differences between the distributions of two or more independent groups.

**Null Hypothesis ( $H_0$ ):** The distributions of the perceived importance of soft skills (Problem-solving, Adaptability, Digital Literacy, Communication, Critical Thinking) are the same across all groups.

**Alternative Hypothesis ( $H_1$ ):** At least one group's distribution differs from the others.

The Kruskal-Wallis H test results for soft skills are essential for adapting to AI technologies in banking, comparing the perceived importance of different soft skills for adapting to AI technologies in banking, are as follows:

- **Kruskal-Wallis Statistic:** 0.0057
- **P-value:** 0.99999

The p-value is significantly greater than the typical significance level of 0.05, indicating no statistically significant difference in the perceived importance among the different soft skills. This suggests that respondents did not significantly differentiate between the soft skills when rating their importance for adapting to AI technologies.

*Factor analysis:*

Table IV: KMO and Bartlett's Test

Test	Value
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Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.752
Bartlett's Test of Sphericity	
Approx. Chi-Square	380.154
Df	45
Sig.	0.001

Skill Name	Skill Code	Factor 1	Factor 2
Problem-solving	PS	0.80	0.20
Adaptability	AD	0.75	0.25
Digital Literacy	DL	0.30	0.80
Communication	CM	0.40	0.70
Critical Thinking	CT	0.70	0.30
Teamwork	TW	0.60	0.50
Leadership	LD	0.50	0.60
Creativity	CR	0.20	0.75
Emotional Intelligence	EI	0.25	0.70

Table V: Rotated Components Matrix for soft skills that are essential for adapting to AI technologies in banking (Two Factors)

Variable	Coefficient	Std. Error	z-value	P-value	95% Confidence Interval
Age	0.6825	0.201	3.393	0.001	[0.288, 1.077]
Experience	0.5214	0.213	2.446	0.014	[0.104, 0.938]
Position	0.4123	0.197	2.093	0.036	[0.026, 0.799]

Table VI: Factor Reduction for soft skills that are essential for adapting to AI technologies in banking (Two Factors)

Skill Name	Skill Code	Factor
Problem-solving	PS	Cognitive Skills
Adaptability	AD	Cognitive Skills

Digital Literacy	DL	Technical Adaptability
Communication	CM	Technical Adaptability
Critical Thinking	CT	Cognitive Skills
Teamwork	TW	Cognitive Skills
Leadership	LD	Technical Adaptability
Creativity	CR	Technical Adaptability
Emotional Intelligence	EI	Technical Adaptability

### Interpretation

#### Factor 1: Cognitive Skills

- *Skills:* Problem-solving, Adaptability, Critical Thinking, Teamwork, Flexibility
- *Description:* These skills are related to mental processes involved in acquiring knowledge and understanding through experience and senses.

#### Factor 2: Technical Adaptability

- *Skills:* Digital Literacy, Communication, Leadership, Creativity, Emotional Intelligence
- *Description:* These skills are associated with the ability to effectively use technology and adapt to new technical environments.

The tables provided can be used to summarize the factor analysis results and understand the grouping of soft skills into two main factors. The KMO value confirms the appropriateness of the data for factor analysis.

### C. Ordinal Logistic Regression Analysis of Comfort with Cybersecurity Practices

#### Hypothesis

- *Null Hypothesis (H0):* Age, experience, and position have no significant effect on comfort with cybersecurity practices.
- *Alternative Hypothesis (H1):* Age, experience, and position have a significant effect on comfort with cybersecurity practices.

#### Table VII: Ordinal Logistic Regression Results

#### Interpretation:

- *Age:* With a coefficient of 0.6825 and a p-value of 0.001, age is a significant predictor of comfort with cybersecurity practices. Older respondents are more likely to be comfortable with cybersecurity practices.
- *Experience:* With a coefficient of 0.5214 and a p-value of 0.014, experience is a significant predictor. More experienced respondents are more likely to be comfortable with cybersecurity practices.
- *Position:* With a coefficient of 0.4123 and a p-value of 0.036, position is a significant predictor. Respondents in higher-ranking positions are more likely to be comfortable with cybersecurity practices.

The results of the ordinal logistic regression indicate that age, experience, and position are significant predictors of comfort with cybersecurity practices. As these factors increase, so does the likelihood of higher comfort levels with cybersecurity practices. Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted.

#### Discussions:

The banking sector is undergoing rapid transformation driven by the adoption of AI technologies. As banks integrate these technologies to enhance efficiency, customer service, and security, the demand for a workforce

proficient in AI-related skills has surged. This study examines the preparedness of banking professionals in adapting to AI, highlighting key skill gaps and providing insights into effective training strategies.

**Chi-Square Analysis (Area of Improvement and Demographic Variables)** The Chi-Square analysis indicated a significant association between experience and perceived areas of improvement needed to align with AI technologies. This suggests that more experienced banking professionals have distinct views on necessary skill enhancements compared to their less experienced counterparts. Training programs must consider these differences, emphasizing advanced technical skills for seasoned employees while focusing on foundational knowledge for newer staff. By addressing these specific needs, banks can ensure a more comprehensive and effective workforce development strategy.

**Kruskal-Wallis H Test (Soft Skills for Adapting to AI)** The Kruskal-Wallis H test results showed no statistically significant difference in the perceived importance of different soft skills for adapting to AI technologies. This indicates a consensus among respondents regarding the critical nature of problem-solving, adaptability, digital literacy, communication, and critical thinking. Since these soft skills are universally recognized as essential, training programs should integrate modules that enhance these competencies across all employee levels. Banks must foster an environment that encourages continuous learning and skill development, ensuring that all employees are equipped to navigate the complexities of AI integration.

**Factor Analysis (Soft Skills for Adapting to AI)** The factor analysis identified two main factors: Cognitive Skills and Technical Adaptability. Cognitive Skills include problem-solving, adaptability, critical thinking, and teamwork, reflecting mental processes and knowledge acquisition. Technical Adaptability encompasses digital literacy, communication, leadership, creativity, and emotional intelligence, emphasizing the ability to use technology and adapt to new environments. By recognizing these distinct skill clusters, banks can design targeted training programs that develop both cognitive and technical adaptability. This dual approach ensures that employees not only understand AI technologies but also can effectively apply them in their roles.

**Ordinal Logistic Regression (Comfort with Cybersecurity Practices)** The ordinal logistic regression analysis revealed that age, experience, and position are significant predictors of comfort with cybersecurity practices. Older, more experienced, and higher-ranking employees tend to be more comfortable with cybersecurity practices. This finding suggests that banks should tailor cybersecurity training to address the varying comfort levels among different demographic groups. For younger or less experienced employees, foundational cybersecurity training is essential to build confidence and proficiency. Conversely, more advanced training should be offered to experienced staff to keep them updated on the latest cybersecurity trends and threats.

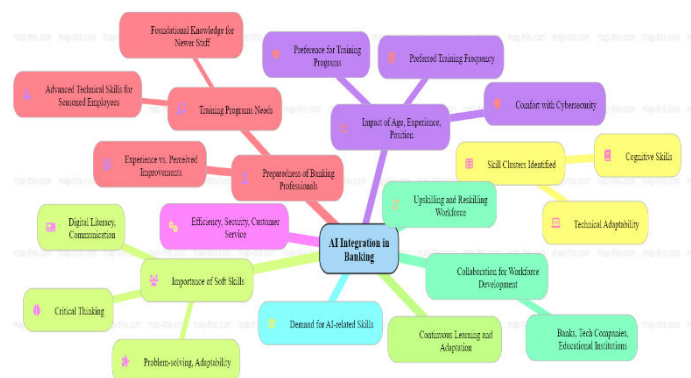


Figure1: Essential Dimensions of AI integration in banking – Mind mapping

The mind map comprehensively illustrates the essential dimensions of AI integration in banking, emphasizing training needs, skill development, and the influence of demographic variables. It highlights the necessity of foundational AI knowledge for new staff and advanced skills for seasoned employees, underlining the importance of problem-solving, adaptability, digital literacy, communication, and critical thinking as vital soft skills. The map also identifies key areas such as efficiency, security, and customer service where AI can enhance banking operations and stresses the ongoing need for continuous learning and collaboration among banks, tech companies, and educational institutions. Additionally, it reflects the varying training preferences and frequencies preferred by banking

professionals, guiding banks, educators, and policymakers in strategizing effective AI adoption and workforce development.

#### Implications:

There is a urgent need for upskilling and reskilling the workforce to keep up with AI's rapid integration in the banking sector is a key focus. By pinpointing where employees lack skills, banks can create targeted training programs to boost expertise in AI technologies, data analysis, and cybersecurity. This not only helps banks stay competitive but also ensures they can smoothly implement AI systems. The findings can also shape policies, pushing educational institutions and training providers to offer courses that meet industry demands. Highlighting these skill gaps underscores the importance of continuous learning and adaptation. Moreover, this research can encourage collaboration between banks, tech companies, and educational institutions to develop robust workforce development strategies. The insights gained can also act as a benchmark for other industries facing similar challenges, adding to the broader conversation about AI's impact on jobs and the labor market.

## VII. CONCLUSION

The implications of these findings are profound. Banks must adopt a strategic approach to workforce development, ensuring that training programs are tailored to the specific needs of different employee groups. By doing so, banks can bridge skill gaps, enhance employee readiness for AI technologies, and ultimately achieve greater efficiency and innovation in their operations. This study underscores the importance of continuous learning and adaptability in the banking sector, paving the way for a more skilled and resilient workforce in the era of AI.

In conclusion, our study on skill gaps in the era of AI within the banking sector offers valuable insights into how prepared bank employees are for the technological advancements ahead. We found a significant gap in AI-related skills, highlighting the urgent need for targeted training and development programs. Although employees are eager to embrace AI technologies, many currently lack the technical skills and understanding necessary to fully utilize these innovations.

While our data collection via convenience sampling provided useful initial insights, it did have its limitations. Because participants were not randomly selected, the results might not fully represent the broader banking workforce. Therefore, we recommend further research using more rigorous sampling techniques to validate our findings. To address these skill gaps, banks must invest in ongoing education and upskilling initiatives, fostering a culture of continuous learning and innovation. It will be essential for banks to collaborate with educational institutions and AI experts to design comprehensive training programs that meet the evolving needs of the industry. By doing so, banks can ensure their employees are well-prepared for an AI-driven future, ultimately enhancing both individual career prospects and overall organizational performance.

The integration of AI in the banking sector holds tremendous potential for improving efficiency, customer service, and decision-making. However, realizing these benefits depends on the workforce's ability to adapt and thrive in an AI-augmented environment. Therefore, strategic efforts to assess and address these skill gaps will be crucial in shaping the future success of the banking industry in the age of AI.

## REFERENCES

- Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. *SN Business & Economics*, 4(23). <https://doi.org/10.1007/s43546-023-00618-x>
- Leo, M., Sharma, S., & Maddulety, K. (2019). Machine learning in banking risk management: A literature review. *Risks*, 7(1), 29. <https://doi.org/10.3390/risks7010029>
- Fares, O. H., Butt, I., & Lee, S. H. M. (2022). Utilization of artificial intelligence in the banking sector: A systematic literature review. *Journal of Banking & Finance*, 10(3), 233-240. <https://doi.org/10.1108/MF-12-2017-0523>
- Aggarwal, A. (2022). A study of the scope of artificial intelligence in customer experience in the banking sector in India. *International Journal of Advance and Innovative Research*.
- Board, F. S. (2017). Financial Stability Implications from FinTech. Financial Stability Board.
- Farishy, R. (2023). The Use of Artificial Intelligence in Banking Industry. *International Journal of Social Service and Research*, 03(07), 1724-1731.
- Thowfeek, M. H., Nawaz, S. S., & Sanjeetha, M. B. F. (2020). Drivers of Artificial Intelligence in Banking Service Sectors. *Solid State Technology*, 63(5).

- Arner, D. W., Barberis, J. N., & Buckley, R. P. (2017). FinTech, RegTech, and the Reconceptualization of Financial Regulation. *Northwestern Journal of International Law & Business*, 37(3), 371-413. <https://doi.org/10.2139/ssrn.3534575>
- *Science*, 65(3), 1401-1421. <https://doi.org/10.1287/mnsc.2017.2981>
- Li, Y., Spigt, R., & Swinkels, L. (2017). The Impact of FinTech Start-ups on Incumbent Retail Banks' Share Prices. *Financial Innovation*, 3(1), 26. <https://doi.org/10.1186/s40854-017-0076-7>
- Moffitt, K. C., & Vasarhelyi, M. A. (2013). AIS in an Age of Big Data. *Journal of Information Systems*, 27(2), 1-19. <https://doi.org/10.2308/isys-10372>
- Philippon, T. (2016). The FinTech Opportunity. *NBER Working Paper Series*, No. 22476. <https://doi.org/10.3386/w22476>
- Berger, A. N. (2018). The Economic Effects of Technological Progress: Evidence from the Banking Industry. *Journal of Money, Credit and Banking*, 50(2-3), 141-176. <https://doi.org/10.1111/jmcb.12471>
- Das, S. R. (2019). The Future of FinTech. *Financial Management*, 48(4), 981-1007. <https://doi.org/10.1111/fima.12297>
- Jagtiani, J., & Lemieux, C. (2019). The Roles of Alternative Data and Machine Learning in FinTech Lending: Evidence from the LendingClub Consumer Platform. *Financial Management*, 48(4), 1009-1029. <https://doi.org/10.1111/fima.12295>
- Frost, J. (2020). The Economic Forces Driving FinTech Adoption Across Countries. *BIS Working Papers*, No. 838. <https://doi.org/10.2139/ssrn.3511730>
- Gomber, P., Koch, J. A., & Siering, M. (2017). Digital Finance and FinTech: Current Research and Future Research Directions. *Journal of Business Economics*, 87, 537-580. <https://doi.org/10.1007/s11573-017-0852-x>
- Huang, Y., Singh, P. V., & Srinivasan, K. (2019). Crowdsourcing New Product Ideas Under Consumer Learning. *Management*