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ARTIFICIAL INTELLIGENCE IN DIGITAL BANKING: APPLICATIONS AND IMPLICATIONS FOR LABOR TRANSFORMATION

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ABSTRACT

The research examines the primary applications of Artificial Intelligence (AI) in digital banking and evaluates their impact on labor market dynamics within the banking industry. The research combines bibliometric analysis using RStudio and VOSviewer, along with qualitative synthesis and content analysis. The results show a significant increase in research on AI and its impact on the banking workforce since 2019, with participation from many countries in both developed and emerging economies, including Vietnam. Furthermore, AI applications focus on three main technology groups: (i) machine learning, including supervised, unsupervised, and deep learning, used in fraud detection, credit risk prediction, and customer behavior analysis; (ii) chatbots and virtual assistants based on natural language processing that support customer service and text data processing; and (iii) robotic process automation (RPA) combined with AI and computer vision for document verification, identity authentication, and workflow management. The study also indicates that AI is driving a skill polarization trend in the banking industry, with a decrease in demand for routine tasks and an increase in demand for high-skill positions, such as data analysts, AI engineers, and cybersecurity specialists. At the same time, digital transformation requires skill restructuring through upskilling and reskilling programs to develop hybrid capabilities in finance, technology, and data. Therefore, the research recommends that banks strengthen digital skills training and assess the labor implications of AI deployment, while recommending policies to support workforce retraining and promote public-private partnerships to ensure sustainable labor transformation in the banking industry.

Keywords: Artificial intelligence, chatbots, digital banking, labor transformation, machine learning, robotic process automation.

1. INTRODUCTION

In recent years, the rapid development of digital technologies has brought profound changes to the operations of the financial and banking sector. In particular, AI has emerged as a key technology enabling financial institutions to improve operational efficiency, enhance risk management, and innovate service delivery. With its ability to process large volumes of data, identify behavioral patterns, and support real-time decision-making, AI is increasingly applied in banking activities such as fraud detection, credit scoring, risk forecasting, and personalized financial services. According to research by Berg et al. (2020), the use of digital data and machine learning algorithms in financial operations has significantly improved the accuracy of credit assessment models compared to traditional methods [1]. This highlights

AI's potential to enhance decision-making efficiency in banking. Additionally, Hilal et al. (2022) note that advanced machine learning techniques and data analytics play a critical role in detecting financial fraud, enabling institutions to identify unusual transactions more quickly and accurately [2]. These developments demonstrate that AI is not just a support tool but is gradually becoming a foundational technology in the modern financial ecosystem.

Alongside the rise of AI, digital banking models are increasingly being adopted by financial institutions to meet customers' growing demand for fast and convenient financial services. Digital banking allows customers to perform a wide range of financial activities, such as payments, money transfers, account management, and lending, through online platforms or mobile devices. The expansion of digital banking not only changes the way financial services are delivered but also drives the adoption of intelligent technologies such as AI, big data, and cloud computing within banking operations. Research by George et al. (2023) indicates that integrating machine learning algorithms into digital banking systems enhances fraud detection capabilities and improves risk management efficiency for online transactions [3]. At the same time, intelligent systems such as chatbots and virtual assistants help banks provide continuous customer support, reduce processing times, and improve user experience. Other studies also emphasize that AI contributes to automating many banking processes, from credit processing and customer data analysis to transaction monitoring (Hilal et al., 2022) [2]. However, alongside operational efficiency and service innovation, the application of AI in digital banking also raises significant issues related to changes in the labor structure of the banking sector. As automation systems and intelligent algorithms are widely implemented, many routine or rule-based tasks tend to be replaced by technology. According to Brynjolfsson and McAfee (2014), the development of digital technologies and AI is transforming the nature of many types of jobs, particularly those that can be automated through algorithms and intelligent systems [4]. This view is further supported by Frey and Osborne (2017), who note that a substantial share of current occupations could be affected by automation in the future [5].

In banking, this shift is clearly reflected in the decreasing demand for manual or repetitive positions, while demand grows for roles related to data analysis, information technology, and digital system development. As banks advance their digital transformation strategies, the workforce must adapt to new skill and knowledge requirements. Research by Ewim et al. (2021) shows that digital transformation in banking significantly changes competency requirements, with digital technology skills, data analysis abilities, and adaptability to digital working environments becoming increasingly important [6]. Skills related to data, technology, and analytical thinking are, therefore, becoming core competencies for the workforce in the financial and banking sector. This indicates that AI adoption not only changes how financial institutions operate but also drives a shift in labor structure and skill requirements.

Moreover, implementing AI in banking operations poses considerable challenges regarding workforce training and development. Morandini et al. (2023) note that the widespread use of AI in organizations increases the need for upskilling and reskilling programs to help employees adapt to new job requirements in a technology-driven environment [7]. Some studies also warn that automation and AI applications may replace certain types of labor, especially routine or standardized tasks [8]. In a rapidly changing technological context, financial institutions need to develop workforce training and retraining strategies to help employees adapt to digital work environments. At the same time, educational and research institutions should update curricula to integrate financial knowledge with technological and data analytics skills, preparing a workforce suited to the development of digital banking in the future.

From these changes, it is evident that AI plays a crucial role in shaping the development of digital banking as well as the labor market in the financial sector. However, although many studies have examined AI applications in banking, research that simultaneously analyzes technological advancement and its implications for labor transformation within the banking sector remains limited. Prior studies have primarily focused on operational outcomes such as service efficiency, fraud detection, customer satisfaction, and risk management, while comparatively less attention has been paid to workforce restructuring, job redesign, and evolving competency requirements within banking institutions. Moreover, studies addressing automation and employment effects often adopt a broad economy-wide perspective rather than examining the specific institutional context of banking, where regulatory compliance, strict data privacy and cybersecurity standards, high ethical expectations in AI deployment, customer trust, and service quality requirements may shape labor transformation in distinct ways.

Based on this context, this study focuses on analyzing typical applications of Artificial Intelligence in digital banking while discussing the impacts of this technology on labor shifts in the banking industry and further provides recommendations for managing workforce transformation and skill development to ensure a sustainable and effective adoption of AI in banking operations.

2. LITERATURE REVIEW

2.1. Artificial Intelligence in Digital Banking and Technology Acceptance Theories

AI refers to computer systems capable of learning from data, recognizing patterns, and supporting decision-making processes through algorithms and computational models [9]. Unlike traditional programmed systems, AI can improve its performance through learning from data, thereby enhancing the accuracy and efficiency of information processing. With the ability to handle large volumes of data and perform real-time analysis, AI increasingly serves as a core technology driving digital transformation in the banking sector, especially amid rising competition and growing demand for personalized services. According to the Technology Acceptance Model proposed by Davis (1989), the acceptance and adoption of new technologies in organizations largely depend on users' perceptions of usefulness and ease of use. When technology is perceived as improving work efficiency without requiring excessive effort to operate, the likelihood of adoption increases [10]. In the context of digital banking, AI systems are widely adopted when they contribute to enhancing data processing efficiency, improving risk management capabilities, and supporting data-driven decision-making. In addition, the diffusion and adoption of technology in organizations can be explained through the Diffusion of Innovation theory [11]. According to this perspective, the adoption of a new technology depends on characteristics such as relative advantage, compatibility with existing systems, complexity, trialability, and observability. In the banking sector, AI is recognized as a technology with clear advantages over traditional analytical methods due to its ability to process data quickly and accurately. When banks perceive the benefits of AI in improving operational efficiency and reducing risks, the diffusion of adoption accelerates throughout the financial system. Moreover, the development of financial technologies has strongly promoted the integration of advanced technologies into banking operations. Research by Gomber et al. (2017) shows that the combination of fintech with AI, big data, and cloud computing is reshaping the operational models of financial institutions [12]. In digital banking environments, AI plays a key role in automating business processes, supporting data-driven decision-making, and providing innovative solutions in financial services.

However, the integration of AI with digital banking not only changes how financial services are delivered but also raises new issues related to labor organization and skill requirements in the banking sector. Automating traditional processes may reduce the demand for routine positions while increasing the need for technology- and data-related skills. Nikolić and Sredojević (2025) indicated that in the banking industry, automation and AI are reshaping employee roles, requiring greater adaptability, digital competencies, and continuous reskilling among bank personnel [13]. In addition, the adoption of AI and robotics has been associated with changes in workforce performance and the increasing importance of technology-enabled work processes in banking operations [14]. Therefore, examining the impact of AI in banking requires not only a technological perspective but also theoretical frameworks addressing labor market transformations under technological advancements.

2.2. Labor shifts under the impact of technology

The rapid development of technology, especially AI, has significantly changed labor market structures. The Skill-Biased Technological Change (SBTC) theory provides a useful analytical framework to explain this phenomenon. According to Katz and Murphy (1992), technological progress tends to increase the demand for high-skilled labor while reducing demand for low-skilled labor, leading to labor market polarization and rising income inequality [15]. This approach suggests that technology does not affect labor neutrally but favors groups able to adapt to new skill requirements. Subsequent studies have expanded this theory. Acemoglu (2002) emphasized that technological progress, particularly in information technology, enhances the productivity of skilled labor, while Violante (2008) noted that technological change can widen wage gaps through skill accumulation and technological advantages [16], [17]. Accordingly, highly educated labor tends to benefit more from technological innovations, whereas workers performing routine tasks are more susceptible to replacement.

In the context of digital banking, this theory is particularly relevant for explaining AI's impact on labor shifts. The application of AI in automating business processes, transaction handling, and data analysis reduces demand for administrative and routine operational positions while increasing demand for technology, data, and risk management-related skills. This clearly reflects the skill-biased nature of technology in the modern banking sector. Additionally, the Task-Based Framework complements this approach by considering production as a set of tasks allocated between labor and technology [18], [19]. Rather than classifying labor solely by skill level, this framework focuses on the nature of tasks, distinguishing between routine and non-routine tasks. Technology tends to replace routine tasks while complementing or creating new tasks with higher value added. Recent research by Acemoglu and Restrepo (2018) indicates that technology generates not only displacement effects but also restructuring effects by creating new tasks and jobs [20]. This implies a dual impact of technology on the labor market, simultaneously reducing some traditional jobs and generating new opportunities that require higher skills.

In banking, this framework explains how AI can replace repetitive tasks such as fraud detection, document processing, or transaction checking while creating new roles such as data analysis, system monitoring, and technology risk management. Consequently, the workforce in the banking sector needs to engage in retraining and upskilling to meet the increasing demands of the digital environment.

3. METHODOLOGY

This study employs a mixed-methods approach combining bibliometric, qualitative analysis, and content analysis to explore the main applications of AI in digital banking and assess their impacts on labor shifts in the banking sector.

3.1. Bibliometric analysis

Bibliometric analysis is applied to identify research trends and the knowledge structure related to AI and the labor market in banking. Data were collected from the Scopus database through queries in article titles, abstracts, and keywords. Specifically, the study used TITLE-ABS-KEY searches with keywords such as "Artificial Intelligence," "banking," and labor-related terms like "labor," "employment," "workforce," and "automation," combined using AND/OR operators to ensure comprehensiveness and relevance.

To improve dataset accuracy, results were further limited to the banking domain, filtering out unrelated studies and ensuring representativeness and reliability for quantitative analysis. The inclusion criteria comprised: journal articles, conference papers, and review papers indexed in Scopus; publications written in English; and studies explicitly related to AI applications in banking or their labor market implications. The exclusion criteria included: duplicate records; publications unrelated to the banking or financial services sector; studies focusing solely on technical algorithms without banking relevance; and documents lacking sufficient bibliographic information. After the screening and filtering process, a total of 474 publications were identified from 2015 to 2025.

RStudio was used to process and statistically analyze bibliometric indicators, including publication trends over time, country distribution, and keyword frequency, leveraging its capacity for large-scale data handling and flexible quantitative analysis. VOSviewer was employed to visualize knowledge structures through network maps, including co-occurrence networks of keywords and research linkages between countries, enabling identification of key themes and levels of collaboration in AI research in banking. This approach allows identification of prominent trends, the development of research topics over time, and the participation of countries across both developed and developing economies, providing a foundation for further analysis of specific AI applications and their impacts on labor shifts in banking.

3.2. Qualitative analysis

The qualitative analysis aims to clarify the content and trends of AI applications in digital banking as well as their impacts on labor shifts. Selected documents were read and thematically coded, focusing on aspects such as technology type, application domain, and labor skill impacts. Based on this, content was categorized and synthesized into main groups to identify prominent trends in AI applications and related changes in employment structures in banking.

The synthesis is organized into three principal thematic groups. First, technology type, including machine learning, chatbots and virtual assistants, natural language processing, robotic process automation, computer vision, and predictive analytics. Second, application domain, including fraud detection, credit scoring, customer service, risk management, operational automation, onboarding processes, and personalized financial services. Third, labor-related impacts, including routine job displacement, task redesign, demand for digital competencies, reskilling needs, hybrid skill formation, and organizational adaptation.

Based on the synthesis of these thematic groups, the study derives practical implications and policy recommendations grounded in three criteria: the recurrence of evidence across studies, the consistency of findings from multiple sources, and the relevance of conclusions to the context of digital banking transformation. Therefore, qualitative analysis complements bibliometric results by providing a more comprehensive understanding of both technological development and labor restructuring associated with AI in the banking industry.

3.3. Content analysis

Content analysis was applied to systematize evidence from the literature and link empirical findings to theoretical frameworks on labor shifts under technological influence. This approach allows the study not only to describe trends but also to provide a basis for explaining changes in skills and labor structure in the context of digital transformation in the banking sector.

The analysis focused on organizing evidence into key content categories, including the automation of routine tasks, changes in employment structure, rising demand for digital and analytical skills, workforce reskilling needs, and the emergence of new technology-related roles in banking organizations. Through comparison across studies, common trends and differences in findings were identified, particularly between developed and developing economies.

In addition, the extracted evidence was interpreted in relation to relevant theoretical perspectives, especially Skill-Biased Technological Change (SBTC) and the Task-Based Framework. This helped explain how AI may simultaneously substitute routine labor, increase demand for skilled employees, and create new occupations associated with data management, AI supervision, and digital operations.

Therefore, content analysis enables the study not only to describe current trends but also to provide a structured basis for explaining changes in skills, job roles, and labor structure in the context of digital transformation in the banking sector.

4. RESULTS

4.1. Global research trends on AI applications in digital banking and labor structure shifts

In recent years, the application of AI in digital banking and its impact on labor markets have attracted growing attention from scholars worldwide. Understanding global research trends helps to identify the evolution of interest and the development of knowledge in this field.

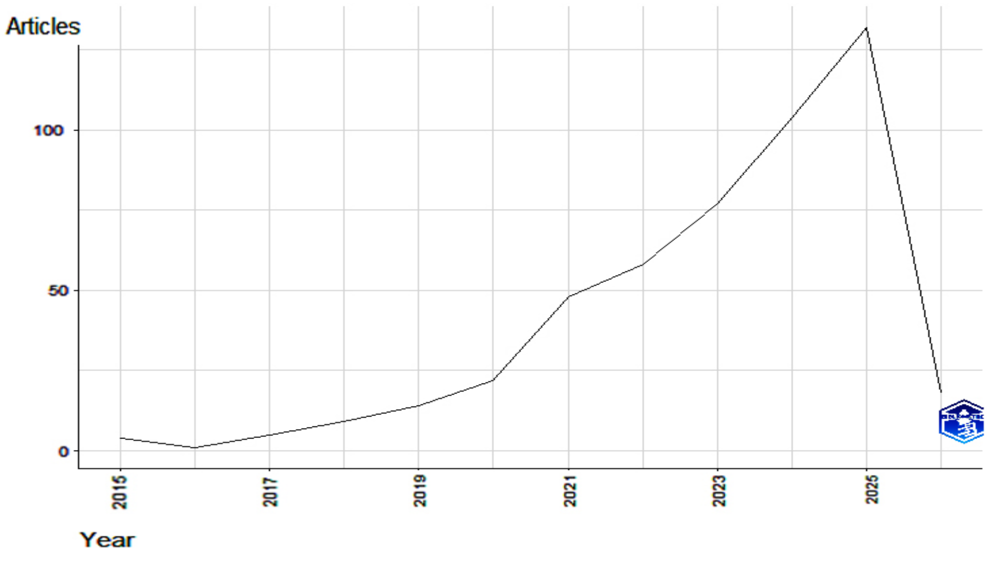


Figure 1. Annual scientific production

Source: Authors' analysis based on Scopus database using R-Studio

The analysis results indicate a clear upward trend in the number of publications related to AI in banking and labor markets over time. During the early period from 2015 to 2018, research output was relatively limited, ranging from 1 to 9 publications per year, reflecting initial low interest and the fact that this topic had not yet become a central focus of study. From 2019 onwards, the number of publications increased rapidly, reaching 14 in 2019 and 22 in 2020. The significant increase in publications after 2019 is closely associated with the rapid adoption of AI technologies and the expansion of digital transformation in the banking sector, which have reshaped financial services and stimulated growing academic attention. In parallel, concerns regarding the impact of AI and automation on labor markets and employment structures have further intensified scholarly interest in this field [5], [21].

Notably, the period from 2021 to 2025 witnessed a sharp rise in research output, with 48 publications in 2021, 58 in 2022, 77 in 2023, and peaking at 132 publications in 2025. This trend demonstrates the growing academic interest in the role of AI in banking, particularly in the context of digital transformation and the rapid development of technologies such as machine learning, natural language processing, and process automation. Overall, the results suggest that research on AI in banking and its effects on labor is entering a strong growth phase, characterized by a rapid increase in publications and significant expansion in research scope.

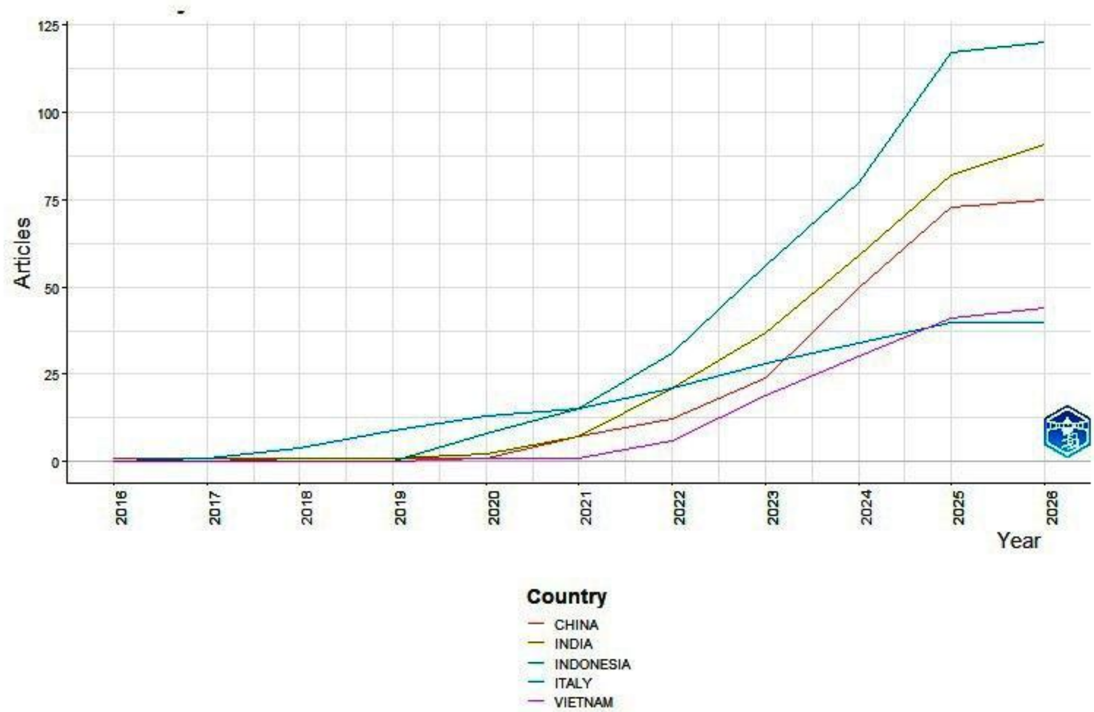


Figure 2. Top Countries Publishing Research

Source: Authors' analysis based on Scopus database using R-Studio

The list of top publishing countries reveals significant differences in both the scale and growth rate of research output. China stands out as the leading country, maintaining a dominant position with rapid growth, particularly after 2020, highlighting its pioneering role in AI research linked to labor markets. In addition, Indonesia and India are emerging as dynamic research hubs, showing the fastest growth in publication numbers, with Indonesia even surpassing others in total publications during the later period. This reflects the increasing attention of developing economies to the impact of AI on employment and labor structure. According to Klapper et al., mobile-phone technology has significantly expanded access to financial accounts and digital payments in low- and middle-income economies [22]. This trend provides a favorable environment for adoption in financial services and, in turn, has stimulated research interest in employment transformation, labor restructuring, and digital banking development across developing countries.

Meanwhile, Italy demonstrates steady growth over the years, representing a developed country with a stable research foundation but without explosive growth. Although Vietnam still has a limited number of publications, it has shown notable improvement in recent years, indicating potential for future development. Overall, the leading countries not only exhibit growth in research volume but also reflect a global trend of increasing attention to AI's impact on labor markets, with developing nations gradually narrowing the gap with early movers.

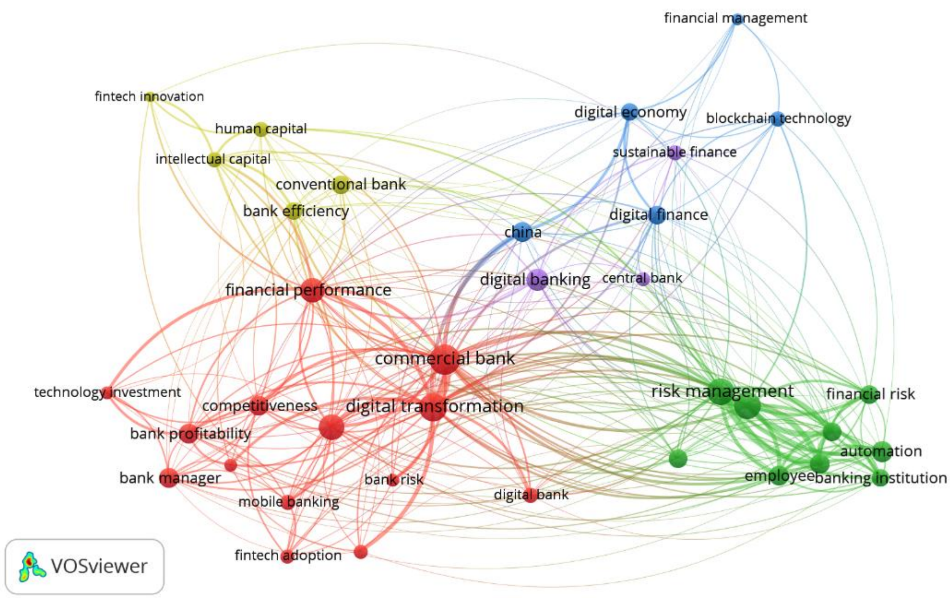


Figure 3. Keyword Co-occurrence Network

Source: Authors' analysis based on Scopus database using VOSviewer

The co-occurrence network of keywords indicates that research on AI applications and labor shifts is structured around five main thematic clusters, reflecting diverse approaches within this field. The cluster centered on "digital transformation" and "commercial bank" highlights the focus on digital transformation processes in the banking sector, where AI is deployed to optimize operations and enhance management efficiency. Closely linked, the cluster including "risk management" and "automation" reflects interest in applying AI for process automation and risk control, contributing to changes in traditional operational practices. At a broader level, the cluster encompassing "digital economy," "digital finance," and "blockchain technology" represents the context of the digital economy, in which AI serves as a foundational technology driving innovation and restructuring economic activities. Simultaneously, the cluster containing "financial performance," "bank profitability," and "technology investment" emphasizes economic efficiency, indicating that AI applications not only provide technical benefits but are also closely tied to optimizing profitability and operational performance. Additionally, the cluster including "human capital" and "intellectual capital" focuses on the human dimension, highlighting the increasing demand for skills, knowledge, and adaptability of the workforce in a rapidly evolving technological environment. Overall, the structure of these keyword clusters not only identifies the main research directions but also clarifies the interconnections between technology, operational efficiency, and human factors. This provides an important foundation for further analyzing how AI impacts labor shifts in the banking sector, particularly in terms of changing skill requirements, task reallocation, and the redefinition of workforce roles in digital settings.

In summary, bibliometric analysis indicates that research on AI applications and their effects on labor shifts is growing rapidly in both volume and depth. Countries such as China, India, and Indonesia play leading roles with rapid growth rates, while Italy demonstrates stable development, and Vietnam has been gradually increasing its presence in recent years. Meanwhile, the keyword network reflects the main research directions centered on digital transformation, automation, risk management, financial performance, and human capital development. The connections among these themes suggest that the field is gradually forming a more integrated approach, providing a basis for deeper analysis of the relationship between AI adoption and changes in labor structure.

4.2. Applications of AI in Digital Banking

AI applications in digital banking have been developing rapidly through three core technology groups: Machine Learning (ML), Chatbots/Virtual Assistants combined with Natural Language Processing (NLP), and Robotic Process Automation (RPA) integrated with Computer Vision. These technologies not only enhance operational efficiency but also drive labor shifts by reducing routine tasks, increasing demand for digital skills, and redefining employee roles within organizations.

First, Machine Learning serves as the central foundation of the AI ecosystem in the banking sector. ML encompasses supervised, unsupervised, and deep learning algorithms and is widely applied in real-time fraud detection, credit scoring, customer behavior analysis, and operational optimization. In Vietnam, major banks such as Vietcombank, Techcombank, and VPBank have actively implemented data analytics and AI solutions to personalize customer services. From a technological perspective, ML hardware performance has grown rapidly over the past decade. As shown in Figure 4, the peak computational performance of ML hardware increased on average by approximately 1.3 times per year and 1.4 times per year between 2008 and 2024. This growth enables the processing of larger data volumes with higher speed and accuracy, thereby facilitating the replacement of many routine tasks previously performed by human workers [23].

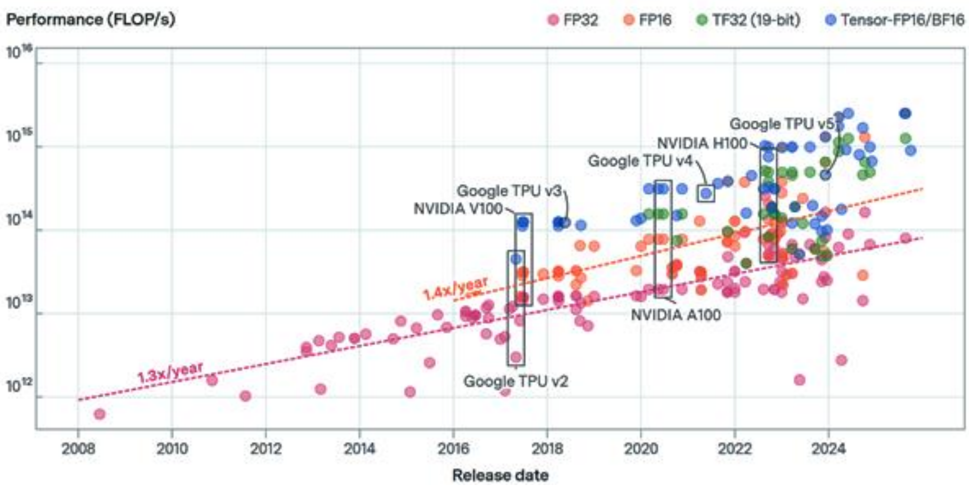


Figure 4. Peak computational performance of ML hardware for different precisions [23]

The surge in computational capabilities not only enhances operational efficiency but also creates an urgent need to upskill the workforce. Banks must invest significantly in upskilling programs, particularly in data analysis, operations, and AI model training.

Second, chatbots, virtual assistants, and Natural Language Processing (NLP) technologies are reshaping how banks interact with customers. By providing basic 24/7 advisory services, automated responses, email handling, and text analysis, these technologies improve customer experience and optimize banking services. Numerous studies highlight the critical role of chatbots in enabling rapid response and personalized interactions [24], [25]. In Vietnam, TPBank pioneered the virtual assistant T'Aio in 2017, while BIDV and MB Bank have also implemented chatbot platforms in their digital banking services. The deployment of these technologies reduces repetitive customer service tasks, allowing employees to focus on higher-value activities such as in-depth financial consulting and handling complex cases. According to Huang and Rust (2018), tasks requiring complex judgment and emotional interaction still need human involvement, whereas simpler tasks can be automated [26].

Third, the integration of RPA, AI, and Computer Vision enables intelligent automation of back-office processes. Typical applications include automated customer onboarding (eKYC), document recognition, fraud detection, and credit processing. Lacity and Willcocks (2016) emphasize that RPA is particularly effective for repetitive processes, delivering high accuracy, reducing operational costs, and improving performance [27]. In Vietnam, VPBank officially deployed eKYC in 2020, while TPBank applied RPA combined with eKYC at scale. These technologies not only replace manual labor but also reshape workforce competency requirements, demanding skills in system monitoring, exception handling, and automated process management. Additionally, studies by Acemoglu and Restrepo (2019) show that new technologies generate tasks related to operating and controlling AI systems, highlighting the dual effect of technology in both replacing and restructuring jobs [28].

From a practical perspective, a report by Finastra (2026) indicates that approximately 94% of banks in Vietnam are increasing investments in AI/ML, with 70% having implemented them in areas such as customer service, marketing, fraud detection, and lending [29]. However, major barriers remain, including data security concerns and legacy system limitations. According to the World Bank (2025), AI is increasing the demand for digital skills in middle-income countries like Vietnam, while significant skill gaps persist, necessitating large-scale workforce retraining strategies [30].

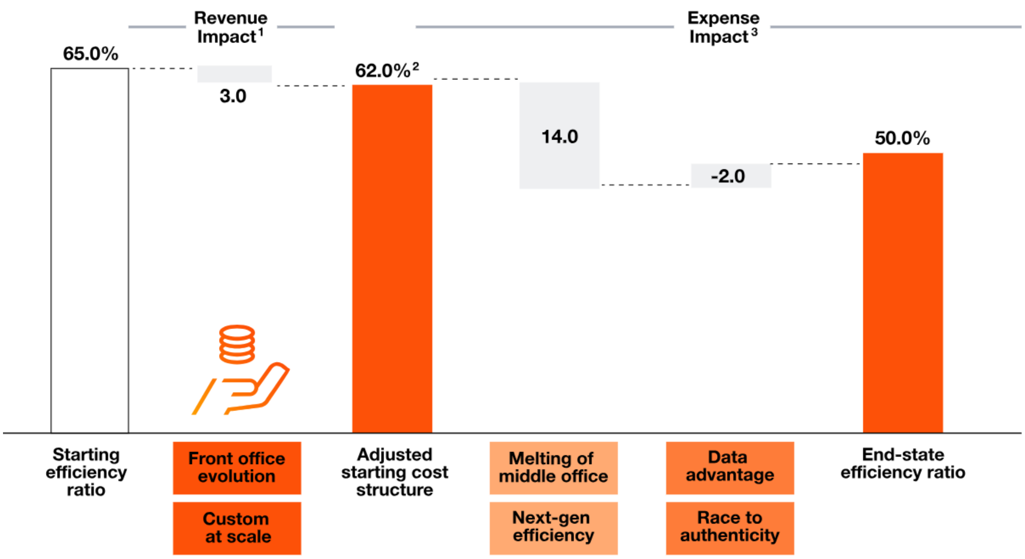
Overall, AI is becoming a core technology enabling digital banking to optimize operations, enhance efficiency, and drive service innovation [31].

4.3. The Impact of AI on labor structure shifts in the banking sector

Analysis based on bibliometric data combined with qualitative synthesis indicates that AI is driving shifts in labor structure within the banking sector along three main directions, in line with foundational theoretical frameworks such as Skill-Biased Technical Change, Routine-Biased Technological Change, and the Task-Based Framework [15], [18], [19].

First, AI is significantly reducing the demand for routine tasks in banking. Technologies such as machine learning, RPA, and NLP increasingly replace easily automatable positions, including tellers, manual document processing, data entry, and administrative work. In practice, Vietnamese banks have implemented AI across activities such as customer service chatbots, automated call centers, and transaction processing, thereby substantially reducing reliance on manual labor. Specifically, Vietcombank and BIDV have deployed chatbots and virtual assistants for customer support, while TPBank and VPBank have scaled digital banking solutions to automate transaction workflows and customer identification processes, effectively streamlining routine operational tasks. According to Do et al. (2022), digital transformation has had a strong positive impact on the performance of Vietnamese banks through process automation and reduced manual labor, particularly evident in large banking institutions [32]. Bibliometric results further support this trend, as keywords such as "automation banking routine" and "clerical displacement" increasingly appear in recent research networks. This aligns with the displacement effect mechanism in the Task-Based Framework, whereby AI substitutes routine tasks, resulting in reduced demand for entry-level or manual labor positions. At the same time, this displacement trend is closely associated with banks' objectives to enhance operational efficiency.

Figure 5. AI Enhancing the Banking Value Chain [33]



According to PwC Strategy&Analysis (2025), comprehensive AI adoption in the banking sector can improve operational efficiency by approximately 15 percentage points [33]. As illustrated, the efficiency ratio initially at 65% could potentially decrease to around 50% in an optimized state, reflecting a substantial enhancement in operational performance. This improvement arises from two dimensions: revenue growth through "front office evolution" and "custom at scale", alongside cost reduction via middle office restructuring, leveraging data advantages and enhancing operational efficiency. Notably, cost improvements account for a larger proportion, highlighting AI's critical role in streamlining processes, automating repetitive tasks, and reducing reliance on manual labor. Therefore, the displacement of routine labor is not merely a consequence of technological progress but is closely linked to strategic initiatives aimed at optimizing operational efficiency and reshaping the banking value chain toward leaner, more effective operations.

Secondly, AI is significantly increasing the demand for digitally skilled and high-level data analytics professionals in the banking sector. Financial institutions increasingly prioritize hiring positions such as data analysts, AI engineers, cybersecurity specialists, and digital banking system administrators, reflecting a clear shift in labor demand structure. This trend aligns with the SBTC theory extensions on skill-biased technology, as AI tends to enhance the productivity of high-skilled workers and contributes to skill polarization [15], [16]. VOSviewer network analysis further supports this observation, showing that keywords like "data analytics banking" and "AI engineer" are strongly linked with "skill demand", indicating a shift from manual labor toward knowledge-intensive and digital-skilled work. In Vietnam, several banks have accelerated data and AI strategies; for example, Techcombank has deployed extensive data analytics and AI across its system to personalize customer experiences and enhance business performance, while Sacombank partnered with Microsoft to develop its AI and data strategy, demonstrating the growing demand for high-tech talent in the digital transformation process. According to the World Economic Forum (2025), by 2030, AI and machine learning are expected to create approximately 170 million new jobs while displacing

92 million jobs globally, yielding a net increase of 78 million positions [34]. Demand for AI/ML specialists is expected to rise sharply, while most companies plan to intensify upskilling and reskilling efforts. In the banking context, routine tasks such as basic customer service, data processing, and administrative activities are increasingly subject to automation, whereas roles requiring analytical skills, technological literacy, and the ability to work alongside AI systems are becoming more important. Recent empirical studies in Vietnam also suggest that digital transformation and AI adoption require substantial adjustments in organizational structure, human resource strategies, and workforce skills [35], [36].

Thirdly, AI drives skill restructuring and increases the demand for workforce reskilling in the banking sector. In Vietnam, this process is progressing rapidly, with approximately 94% of financial institutions planning to increase AI investment and the majority already deploying AI in areas such as customer service, marketing, and internal operations. Banks must invest heavily in upskilling and reskilling programs to help employees adapt to digital transformation. Workers are therefore required not only to have traditional financial knowledge but also to develop hybrid skills, combining technology, data analytics, digital literacy, and the capacity to work with AI systems. Recent studies emphasize that AI highlights the importance of transversal skills such as critical thinking, lifelong learning, complex problem-solving, and human-machine collaboration [7]. Appropriate training strategies allow organizations to leverage the reinstatement effect, where AI not only replaces old tasks but also creates new roles such as AI system supervision, exception handling, and data-driven decision-making [28]. Consequently, the transformation can shift from displacement toward augmentation, reducing technological unemployment risks and fostering high-value job creation. Moreover, AI could displace approximately 6 - 7% of the global workforce in the next decade, with more pronounced impacts in banking roles such as customer service and credit analysis [37]. However, short-term unemployment increases are expected to be limited to around 0.5 percentage points and can be offset if reskilling programs are implemented in a timely manner and at scale.

Overall, AI not only causes displacement in routine jobs but also creates opportunities for labor transformation toward higher-quality work, provided that appropriate training and skill development strategies are effectively implemented.

5. CONCLUSION

5.1. Conclusion and Suggestions

Research indicates that AI is driving a significant shift in the labor structure of the banking sector. Through the combination of bibliometric evidence and qualitative synthesis, the findings provide a broader understanding of how AI implementation in banking simultaneously influences operational efficiency, workforce demand, and organizational transformation, particularly in terms of employment restructuring, skill-biased change, and workforce adaptation. Routine and manual tasks are gradually being replaced by automated systems, while the demand for highly skilled digital labor, data analytics capabilities, and technological literacy is increasing. The workforce is transitioning from entry-level and administrative roles to positions requiring specialized knowledge, technological skills, and the ability to collaborate effectively with AI. This transformation not only changes the operational processes of banks but also creates opportunities for higher-value roles and reshapes organizational and human resource strategies within the sector.

To maximize the benefits of AI while minimizing negative impacts on the workforce, banks and regulatory authorities need to implement coordinated, strategic, and sustainable solutions.

Firstly, financial institutions should develop comprehensive skills transformation strategies, focusing on enhancing existing capabilities through upskilling and reskilling programs, while fostering hybrid skills that combine traditional financial knowledge with data analytics, digital literacy, critical thinking, and the ability to monitor and handle exceptions arising from AI systems.

Additionally, strengthening collaboration with universities, training centers, and specialized educational institutions can help banks update curricula to meet new labor demands, particularly in areas such as AI, big data, and cybersecurity. Banks should also implement large-scale, continuous, and flexible internal training programs. Concurrently, a human-AI augmentation strategy should be adopted, where AI serves as a supportive tool rather than a complete replacement, especially in roles requiring emotional intelligence, judgment, and specialized advisory skills. This approach maintains high-quality employment while enhancing customer experience.

Finally, government authorities need to improve legal frameworks, develop policies supporting workforce retraining, and establish flexible social protection systems to safeguard employees affected by digital transformation. A coordinated combination of human capital development strategies, intelligent AI deployment, and regulatory policies will enable the banking sector not only to enhance competitiveness but also to ensure a sustainable and equitable labor transition, ultimately fostering a high-quality workforce suited for the digital era.

5.2. Limitations and Future Research

Although this study provides valuable insights, several limitations should be acknowledged. First, the research is conducted based on qualitative synthesis and bibliometric analysis, which may limit the empirical validation of the findings. In addition, the study does not incorporate primary data from bank employees or banking institutions, which could provide deeper and more comprehensive practical insights into the impact of AI in the banking sector. Furthermore, the bibliometric analysis is primarily based on the Scopus database; therefore, the scope of literature may not fully cover all relevant studies from Web of Science, Google Scholar, and other open-access academic sources. This may somewhat affect the comprehensiveness of the literature coverage and the inclusion of all relevant studies.

Based on the identified limitations, future research could first address the methodological limitation by combining qualitative synthesis and bibliometric analysis with empirical validation. The inclusion of primary data from bank employees and financial institutions would enhance the practical relevance and robustness of the findings. Besides that, future studies should expand the bibliometric data sources beyond Scopus by incorporating Web of Science, Google Scholar, and other academic databases. This would improve the comprehensiveness of the literature coverage and provide a more complete representation of existing research.

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