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ORGINAL RESEARCH PAPER

Transforming Banks into Digital Organizations: The Effects of Artificial Intelligence on Reducing Branches and Improving Financial Services

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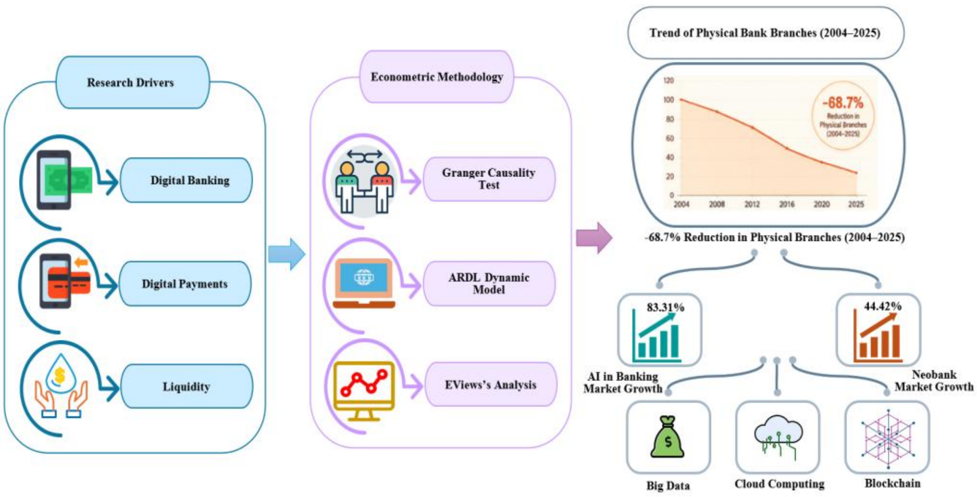
A B S T R A C T

This study investigates the effects of digital banking, digital payments, and liquidity conditions on the number of physical bank branches over the period from 2004 to 2025. The research was conducted using the autoregressive distributed lag econometric method in EViews version 12. The results of the Augmented Dickey–Fuller unit root test indicated that the research variables were non-stationary at level and stationary at the first difference. Based on the Granger causality test, a unidirectional causal relationship from digital banking to digital payments and liquidity was confirmed. The results of estimating the dynamic research model indicate a negative and significant effect of the explanatory variables on the number of physical branches, such that the estimated coefficients for the digital banking index, digital payments, and liquidity were −0.319, −35.37, and −44.71, respectively. These findings demonstrate a substantial reduction in the banking system's structural dependence on physical branches following the expansion of non-face-to-face payment instruments and the development of digital infrastructure. The downward trend in the number of branches accelerated particularly after 2013 and reached its minimum during 2017–2020. Given the projected annual growth rate of 83.31% for artificial intelligence in the financial industry and the 44.42% growth of neobanks by 2033, it is essential for banks to move toward optimizing their branch networks and enhancing virtual services by investing in emerging technologies such as big data, cloud computing, and blockchain.



1. Introduction

The rapid technological transformations of recent years have significantly reshaped the banking industry. Banks, as one of the vital pillars of the global economy, have long sought to improve efficiency, reduce costs, and facilitate service delivery to customers. In this regard, the emergence of new technologies, particularly artificial intelligence, has provided an exceptional opportunity for digital transformation in this industry. This transformation not only leads to technical changes in banking processes, but also opens a new horizon for how services are delivered to customers and how banking resources are managed (Tanwar et al., 2025).

One of the key aspects of this transformation is the change in the way banking services are delivered. In the past, a major portion of banking operations was carried out through physical branches, but now, with the growth of digital technologies, many banking services are provided through online and mobile platforms. This change has accelerated particularly in the post-COVID-19 pandemic period, which led to increased demand for online services. One of the major effects of these developments has been the gradual reduction in the need for physical branches and, consequently, the improvement of access to banking services through digital tools for all segments of society (Ovinyi et al., 2024).

Artificial intelligence, with capabilities such as big data analytics, natural language processing, machine learning, and conversational chatbots, plays a fundamental role in this transformation (Paramesha et al., 2024). The use of these technologies in banks improves internal processes such as financial automation, reduces operational costs, increases accuracy in decision-making, and facilitates customer service delivery. In addition, artificial intelligence can play a role in predicting customer needs and providing personalized services to them, enabling banks to deliver better services to their customers (Blokubasi, 2025).

This study examines the effects of artificial intelligence on the transformation of banks into digital organizations, the reduction of physical branches, and the improvement of financial services over the time horizon of 2030 to 2034. In this regard, forecasts will be presented concerning how the future of the banking industry will be shaped through the use of artificial intelligence and its effects on banking processes, structures, and services. The aim of this research is to identify opportunities and challenges and to provide solutions for banks to optimally utilize emerging technologies in order to enhance efficiency and service quality.

Artificial intelligence (AI) plays a vital role in the banking industry by enhancing system efficiency through improved data analytics, trend and fraud risk forecasting, and increased customer engagement. AI can minimize human error in data analysis, customer onboarding, document processing, customer interactions, and other operational tasks through automated algorithms and processes executed continuously and accurately (Kumar & Threesha, 2024). This technology also assists banks in customer service delivery, fraud detection, and wealth/investment management, ultimately driving the growth of the e-banking market (Manatha et al., 2024). Furthermore, the COVID-19 pandemic served as an accelerating catalyst, creating a favorable environment for AI adoption in banking, as emerging technologies efficiently handled essential remote services and customer registration processes (Abdulsalam & Tajuddin, 2024). The pandemic also accelerated digital transformation via the rapid spread of smartphones. Consumers have increasingly integrated digital technologies into their lifestyle, embracing digital payments, investment tech, fully online insurance, and other aspects of this evolving digital landscape (Atin & Yetgin, 2025).

The application of blockchain-based AI in the banking industry was valued at approximately 349 million in 2022 and is projected to reach 2,787.4 million (approx. $2.8 billion) by 2033, reflecting a compound annual growth rate (CAGR) of 23.1%. This rapid expansion will accelerate after 2028 due to broader blockchain adoption in AI, data security, and decentralized processing (Market.us, 2024).

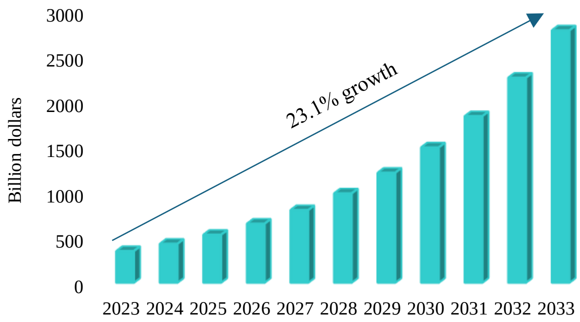


Figure 1. Forecasted Global Market Value of Blockchain-Based AI in Banking and Financial Services (2022–2030)
Source: http://www.market.us/

The global AI market size in banking stood at 19.90 billion in 2023, reached 26.23 billion in 2024, and is projected to expand to approximately $315.50 billion by 2033. The market is growing at a CAGR of 31.83% over the forecast period of 2024 to 2033. Digitalization and the modernization of banking and financial institutions are primary drivers of this market growth (Precedence Research, 2025).

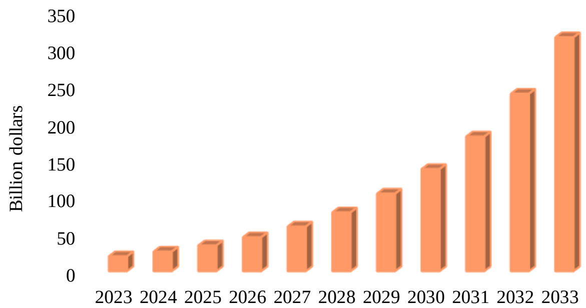


Figure 2. Forecasted Global AI Market Size in Banking and Financial Services (2023–2033)
Source: http://www.precedenceresearch.com/

The global AI market size was valued at 538.13 billion in 2023 and is projected to reach approximately 3,680.47 billion by 2034, expanding at a CAGR of 19.1% from 2023 to 2034. The North American AI market size reached $198.57 billion in 2023 (Precedence Research, 2025).

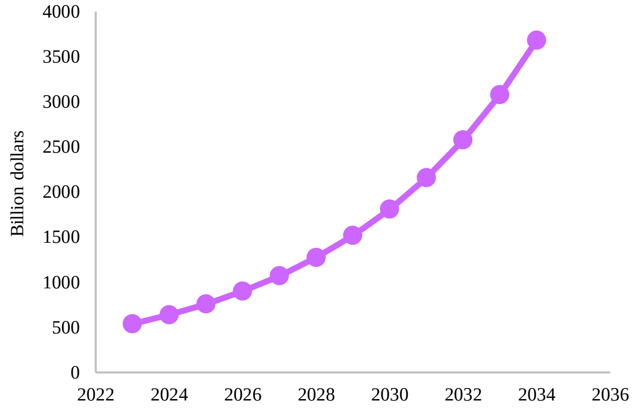


Figure 3. Forecasted Global AI Market Growth Size (2023–2034)
Source: http://www.precedenceresearch.com/

The global generative AI market in banking and finance is estimated at 1,260.16 billion in 2024 and is projected to reach approximately 21,824.46 billion by 2034, growing at a CAGR of 33% during the 2024–2034 forecast period (Precedence Research, 2025).

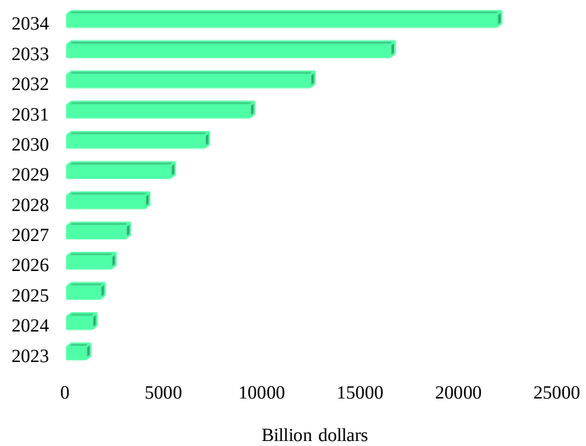


Figure 4. Forecasted Global Generative AI Market Size in B anking and Financial Services (2023–2034)
Source: http://www.precedenceresearch.com/

Machine learning (ML) is a subset of AI technologies designed to learn from data and accurately predict outcomes without explicit rule-based programming. As a data-driven method, ML follows numerous algorithms broadly categorized into supervised learning, unsupervised learning, and reinforcement learning. Recently, due to the multidimensional nature of banking data, ML has been increasingly adopted across the banking sector. The application of machine learning in banking demonstrates that bank performance can be effectively analyzed through a wide spectrum of ML models, transforming the financial sector (Dere et al., 2025; De Chu et al., 2025).

As the financial system rapidly evolves, the presence of digital banking will become even more prominent in the future. Consequently, machine learning technology has become an essential tool in cybersecurity and digital banking by identifying threats and anomalies and preventing fraud (Preciado Martinez et al., 2025). In digital banking, ML primarily detects anomalies that lead to security breaches. By leveraging data mining and AI power, ML applications in banking and financial institutions have developed robust fraud detection systems capable of distinguishing fraudulent from legitimate transactions. Through fast and accurate processing of massive data volumes, ML plays a crucial role in enhancing security measures (Asmar & Togar, 2024; Mishra et al., 2024). Furthermore, ML is widely utilized in banking for credit risk assessment and prediction, fraud detection via real-time transaction pattern analysis, and personalized marketing (Mozumder et al., 2024). As shown in Figure 5, the global ML market in banking and financial services will rise from 2.7 billion in 2023 to 41.9 billion in 2033, representing a CAGR of 31.8% (Market.us, 2024).

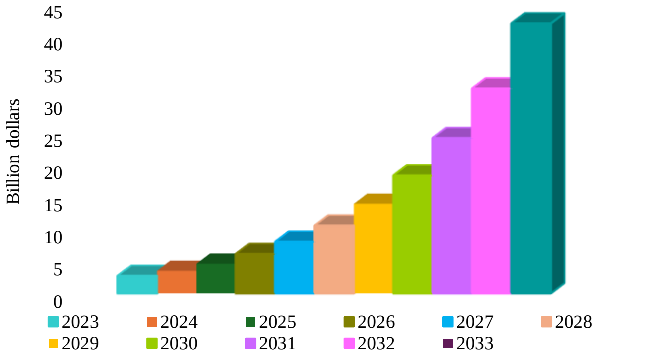


Figure 4. Forecasted Global Machine Learning Market Size in Financial Services (2022–2032)
Source: http://www.market.us/

The global e-banking market size is estimated at 9.50 trillion in 2024 and is projected to reach approximately 15.59 trillion by 2034, growing at a CAGR of 50.8% from 2025 to 2034. High smartphone penetration worldwide, the rollout of 5G smart mobile networks, and the expansion of the banking sector are major growth drivers (Precedence Research, 2025).

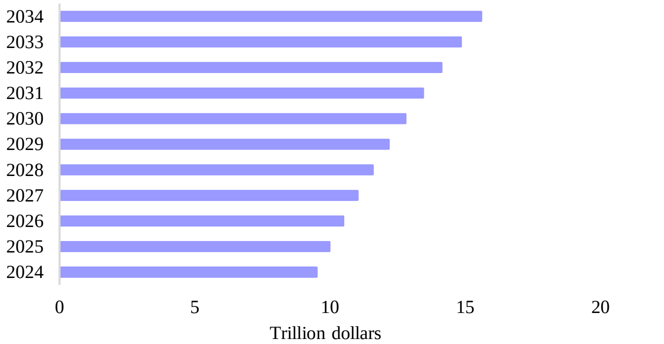


Figure 5. Global E-Banking Market Size (2024–2034)
Source: http://www.precedenceresearch.com/

As shown in Figure 7, estimates indicate that the global market size for digital banking platforms and services will reach approximately 50.5 billion by 2033, up from15 billion in 2023. This market is projected to expand at a CAGR of 12.9% over the 2024–2033 period. The Asia-Pacific region dominated the market in 2023 with a 36.5% share and revenue generation of $5.47 billion (Market.us, 2024).

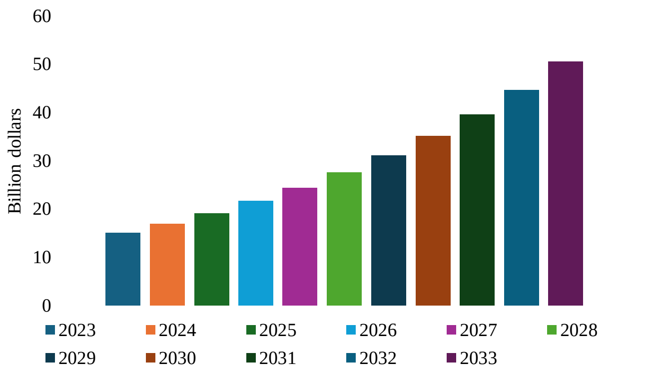


Figure 6. Global Digital Banking Platforms and Services Market (2023–2033)
Source: http://www.market.us/

Recent observations show that 636 branches opened at the beginning of 2023 were closed by December, and total branch counts have dropped from over 10,000 in 2013 to fewer than 5,000 currently. For instance, Figure 8 illustrates significant shifts in US bank branch counts since 2000. Between 2000 and 2012, branch counts rose by 30%, increasing from 63,740 in 2009 to 83,060 in 2012. However, since 2012, branch counts have declined by an average of 902 branches per year. Between 2012 and 2018, branches experienced a net decrease of 5,413 (6.52%), reaching 77,647. In other words, one out of every 15 banks operating in 2012 has closed. Data also reveal that branch closure rates doubled every three years: between 2012 and 2015, the annual closure rate was 0.81%, whereas between 2015 and 2018, it accelerated to 1.6% annually. Based on these trends, branch counts are projected to fall below 40,000 by 2027 and under 16,000 by 2030.

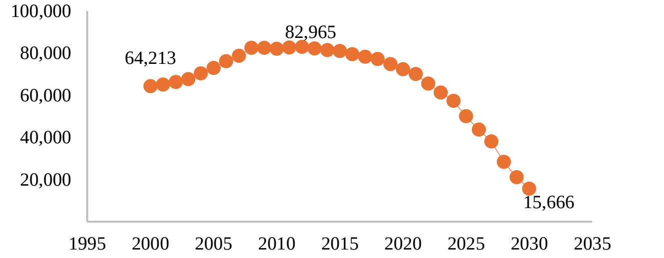


Figure 7. Forecast of US Bank Branch Counts (2000–2030)
Source: www.self.inc

With the advancement of emerging financial technologies such as blockchain and AI, physical bank branches are projected to become extinct by 2034, replaced by neobanks. Neobanks are fully digital, branchless banks delivering seamless services via online platforms. By leveraging technology, they elevate traditional banking experiences, offering easy access to services such as online account opening, deposits, withdrawals, debit card issuance, investment opportunities, lending, and credit services.

Although most neobanks lack an independent banking license and operate through partnerships with licensed banks, their expansion is fueled by rising demand for digitized financial services, FinTech investments, regulatory support, and advanced digital infrastructure. Eliminating physical branches enables neobanks to reduce overhead costs and offer more competitive rates and fees. As shown in Figure 9, the global neobank market was valued at 96.20 billion in 2023 and is projected to reach approximately 3,799.25 billion by 2033, expanding at a CAGR of 44.42% from 2024 to 2033. The neobank market delivers a smooth online and mobile banking experience, allowing users to manage their finances anytime, anywhere via web or mobile apps (Precedence Research, 2025).

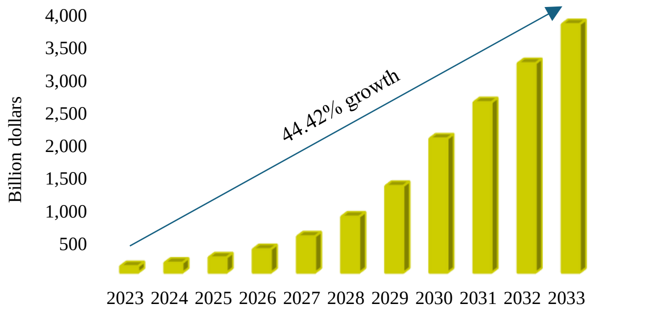


Figure 8. Forecasted Global Neobank Market Size and Growth (2023–2033)
Source: http://www.precedenceresearch.com/

The substantial market share of neobanks can be attributed to growing demand for convenient and efficient payment solutions in the digital age. In this context, neobank market size and growth forecasts were examined for Europe and North America.

As shown in Figure 10, the European neobank market size was estimated at 32.71 billion in 2023 and is projected to reach approximately 1,295.54 billion by 2033, growing at a CAGR of 44.46% during 2024–2033. This growth is driven by regulatory reforms such as the EU's Second Payment Services Directive (PSD2), which promoted open banking and granted third-party providers access to customer account data, easing market entry for newcomers. Customers—particularly younger demographics—were drawn to neobanks due to ease of use, transparency, and personalized financial services (Precedence Research, 2025).

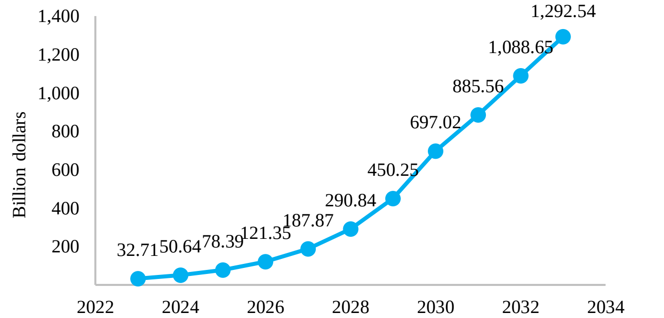


Figure 9. Forecasted Neobank Market Size and Growth in Europe (2023–2033)
Source: http://www.precedenceresearch.com/

Additionally, Figure 11 indicates that the North American neobank market size was estimated at 28.86 billion in 2023 and is projected to reach approximately 1,158.77 billion by 2033, expanding at a CAGR of 44.66% over the 2024–2033 period (Precedence Research, 2025).

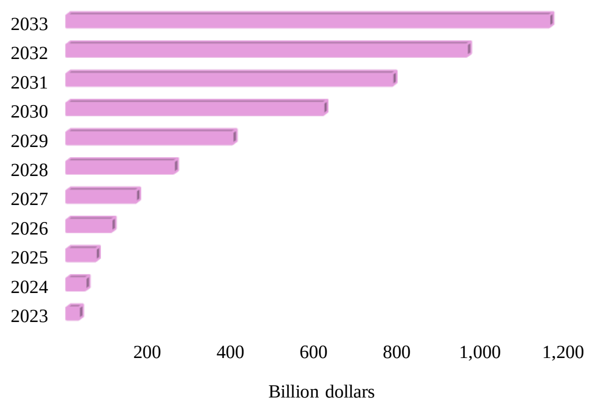


Figure 10. Forecasted Neobank Market Size and Growth in North America (2023–2033)

Source: http://www.precedenceresearch.com/

In recent years, neobanks have rapidly grown and attracted global customers by delivering digital banking services and an enhanced user experience. Table 1 lists the top 10 neobanks in the world in 2025.

As shown in Figure 12, the growth in the number of users of neobanks worldwide indicates that the key success factors of neobanks include offering specialized services, low fees, and a technology-centered user experience. This growth trend clearly reflects a shift in users' preferences toward digital banking and remote (non-branch) services.

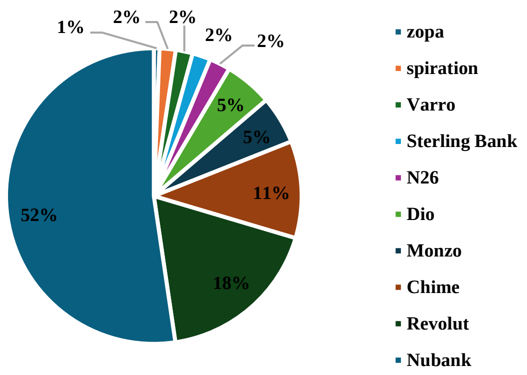


Figure 11. User Count of the Top 10 Neobanks in the World in 2025 (Millions of Users)

Source: international.nubank.com.br, www.businessofapps.com, prioridata.com, monzo.com, www.emarketer.com, techcrunch.com, www.statista.com

Data analysis of the top 10 neobanks in 2025 indicates that their rapid user growth stems from three key factors:

- Complete focus on digital services and the elimination or minimization of physical branches;
- Extensive utilization of AI in customer relationship management (CRM) and credit assessment;
- Design of a simple, personalized, and low-cost user experience (UX).

Table 1. Top 10 Neobanks in the World in 2025

Neobank	Launch Year	Number of Users	Specialization / Focus
Nubank	2013	110 million	One of the largest FinTech companies in Latin America.
Revolut	2015	38 million	Known for providing international money transfers with minimal fees.
Chime	2012	22.3 million	A user-friendly neobank for personal and business use.
Monzo	2015	11 million	Offering a wide range of banking services, including savings and loans.
Dave	2014	11 million	The first digital bank to offer loans and savings accounts.
N26	2013	4.8 million	A European-based neobank popular for low fees and mobile user experience.
Starling Bank	2014	4.2 million	A UK-based neobank focusing on small businesses.
Varo	2015	3.9 million	A US-based neobank offering a zero-fee banking solution.
Aspiration	2014	3.7 million	Known for its environmental focus and socially conscious banking.
Zopa	2005	1.3 million	Originally a peer-to-peer lender, now offering a range of neobank services.

Source: international.nubank.com.br, www.businessofapps.com, prioridata.com, monzo.com, www.emarketer.com, techcrunch.com, www.statista.com

User metrics reveal that neobanks have achieved massive scale without expanding physical infrastructure, signaling a paradigm shift from branch-centric to platform-centric banking. Furthermore, findings indicate that AI in neobanks is predominantly deployed in:

- Customer behavior analysis and personalized financial product recommendations;
- Real-time credit assessment for micro-loans;
- Fraud detection and risk management;
- Automated support services via chatbots.

These applications have resulted in reduced operational costs, increased service speed, and enhanced customer satisfaction.

Comparative findings demonstrate a significant relationship between AI adoption levels and the declining role of physical branches. Banks that leveraged data analytics, process automation, and smart services have:

- Reduced in-person branch visits;
- Converted a portion of branches into advisory hubs or complex service centers;
- Decreased physical infrastructure maintenance costs.

In neobanks, this trend has led to the complete elimination of branches, whereas in traditional banks, it has resulted in a redefinition of branch functionality. Thus, a key insight of this research is that AI does not necessarily trigger an immediate elimination of branches, but rather redefines their role first.

According to Central Bank reports, over 62,000 ATMs were active across Iran by the end of 1402 SH (March 2024), with approximately 22% located in Tehran and 78% in other cities. Bank Melli Iran holds the largest share among domestic banks with 8,372 ATMs, followed by Bank Saderat (5,186) and Bank Mellat (4,526) (Bank Melli Iran, 2024).

Additionally, over 450 million bank cards had been issued nationwide by the end of 1402 SH, with roughly 128 million cards distributed in Tehran and 322 million in other cities. Bank Melli Iran leads with 94,817,637 issued cards, followed by Bank Mellat (59,741,680) and Bank Saderat (49,780,583) (Bank Melli Iran, 2024).

Table 2. Applications of Domestic Iranian Banks

Bank	Application	Launch Year	Number of Users	Specialization / Focus
Melli	Bale	2016	13 million	Combination of social messaging and financial payment/transaction services
	BAM	2015	12 million	Bank account management and online banking operations
	Iva	2016	6 million	Virtual branch of Bank Melli, corporate payments, insurance, financial, and payment services
Mellat	Sekeh	2017	4 million	Online branch queueing for Bank Mellat, Digital Rial, loan repayments, etc.
	Megabank	2023	3 million	Combination of social messaging and financial payment/transaction services
Saderat	SAP	2018	3 million	Various financial services, dynamic OTP generator, ETF subscription fund, barcode generator, etc.
Parsian	TOP	2015	7 million	Stock market, insurance, FinTech, payments, etc.
Saman	Blu Bank	2019	10 million	Domestic digital banking and neobank
Middle East	Bankino	2019	350,000	Account opening, micro-loans, fixed-income fund investments, etc.
Pasargad	Wepod	2020	3 million	Domestic digital banking and neobank
Ayandeh	Abank	2021	2 million	Domestic digital banking and neobank

Source: baam.bmi.ir, rooydadejadid.ir, blog.bale.ai, ivaapp.com, sekeh.behpardakht.com, megabank.bankmellat.ir, apps.bsi.ir, top.ir, blubank.sb24.ir, bankino.digital, wepod.ir, abankapp.ir

As illustrated in Table 2, Bank Melli Iran plays a leading role in digital banking by offering three major applications: Bale (13 million users), BAM (12 million users), and Iva (6 million users). Bale combines social messaging with financial services, BAM serves as an account management platform, and Iva operates as a virtual branch. Compared to Blu Bank (10 million users) and TOP (7 million users), Bank Melli can reinforce its position by investing in FinTechs and emerging technologies such as blockchain and smart payments. Implementing AI within Bank Melli will not only boost efficiency but also serve as a benchmark for digital transformation across the Iranian banking system. As one of the largest and oldest banks in the Middle East, Bank Melli Iran holds a unique standing in the digital transformation era. Given its extensive infrastructure, robust financial and human resources, and large client base, it can become a primary pioneer in AI adoption within Iran's banking system.

Table 3 demonstrates that the primary gap between Iran and global trends lies not in the existence of digital services, but in the level of AI maturity, data-driven decision-making, and digital-first banking architecture. Consequently, the future trajectory of Iranian banks is expected to be gradual and converging toward global models.

Table 3. Comparison of Iranian Banks' Status with Global Trends in Digital Transformation and AI Application

Axis of Comparison	Global Trends (Neobanks & Leading Banks)	Status of Iranian Banks
Digital Transformation Stage	Fully digital and platform banking with minimal reliance on physical infrastructure	Transition stage from traditional to digital banking and continuation of a hybrid model
Service Architecture	Digital-first design and integrated mobile-centric service delivery	Gradual digitalization of traditional structure and multi-platform service delivery
Diversity of Digital Services	Broad spectrum of smart services including instant lending, personal financial management, and investment	Main focus on payments, money transfers, and account management; more limited smart services
Neobanks	Neobanks are the dominant modern banking model and often branchless	Creation of pseudo-neobank examples and testing branchless models in certain banks
Role of Data in Decision-Making	Complete data-driven approach and algorithmic decision-making	Predominantly process-driven with more limited use of advanced data analytics
Application of AI	Widespread application in personalization, automated credit scoring, fraud detection, and predictive banking	Early-stage applications including semi-smart credit scoring, fraud detection, and chatbots
Service Personalization	Advanced personalization and real-time financial product recommendations	Limited personalization, mostly based on predefined rules
Role of Branches	Elimination or minimization of branches and converting them into advisory centers	Reliance on a hybrid model and continuation of an extensive branch network
Physical Infrastructure	Reduced reliance on cards and ATMs, moving toward fully digital banking	High number of bank cards and ATMs indicating continuation of traditional infrastructure
Impact of AI on Service Quality	Significant reduction in service time, increased accuracy of credit decisions, and higher customer loyalty	Gradual improvement in speed and user experience with less intensity compared to global trends
Structural Consequences	Shift in staff roles toward data analysis, extensive collaboration with FinTechs, and platform banking	Beginning of human resource role transition, increased FinTech collaboration, and gradual movement toward a platform model
Future Path	Consolidation of branchless and predictive banking	Phased transformation toward digital and potential long-term transition to a platform model

Source: Research Findings

The findings indicate that global banking transformation has pivoted toward fully digital, data-driven, and AI-powered models, with neobanks becoming the dominant blueprint for reducing branch dependence and offering hyper-personalized services. In contrast, while Iranian banks have made significant progress in developing mobile applications and remote services, they remain in a transition phase dependent on traditional infrastructure, with more limited AI maturity and data analytics capabilities. This gap underlines that transformation in Iran will follow a gradual trajectory, necessitating a redesign of service architecture, strengthened data analytics, and expanded AI deployment. Overall, the future of the Iranian banking system hinges on strategic movement toward platform banking, reducing the operational role of branches, and broader utilization of AI to elevate financial service quality and operational efficiency.

2. Method

The methodology section delineates the logical structure and analytical framework employed to achieve the study's objectives and test the primary hypotheses. This research focuses on analyzing the long-term and short-term relationships between digital transformation (encompassing digital banking and digital payments) and the physical structure of banks (number of branches).

2.1. General Research Approach

From the perspective of purpose, this research is applied, as it seeks to provide practical solutions for the banking industry in the face of digital transformation and artificial intelligence. In terms of nature and method, it is a descriptive-analytical study utilizing a quantitative approach based on econometric time-series analysis.

The econometric approach enables the researchers to not only describe observed relationships but also conduct causal testing and determine the magnitude and direction of the independent variables' impact on the dependent variable over a specific time horizon. This necessitates the use of advanced modeling, specifically the Autoregressive Distributed Lag (ARDL) model, to ensure the results possess the precision and validity required for strategic decision-making.

2.2. Statistical Population and Research Sample

The statistical population of this research consists of macro data related to banking activities and macroeconomic indicators at a global level or within a major economy. Since this study is based on time-series analysis, a specific time range is selected as the study period instead of sampling individuals or firms. The research period is set from 2004 to 2025. This interval was chosen for two primary reasons:

- The year 2004 coincides with the significant expansion of high-speed internet infrastructure and the serious entry of the first instances of electronic banking globally.
- The end of the period in 2025 allows for the use of the latest available data and, where necessary, the inclusion of short-term forecasts for the final year.

The collected data is annual, providing a total of 22 time-series observations for analysis.

2.3. Data Collection Tools

The primary tool for data collection in this research is secondary documents and records. The required data has been extracted from the following official, reputable international sources to ensure reliability and international comparability:

- World Bank Data: Primarily used for extracting indicators related to macro-economic and financial infrastructure, regulation, and general liquidity metrics.
- Federal Reserve Economic Data (FRED): A vital source for accessing precise time series related to the macroeconomy, monetary and financial indicators, and metrics related to financial system stability.
- Statista Official Reports: Used to collect specific and up-to-date data on digital technology adoption trends, digital payment transaction volumes, and statistics regarding the reduction or increase of bank branches in the targeted global or regional scope.

Since the research follows an econometric approach, raw data, once collected, was organized into regular time series and underwent preliminary validation to ensure consistency and eliminate discrepancies.

2.4. Model Introduction and Data Analysis Tools

The primary analytical model for this research is the Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al. (2001). This model was chosen for its unique capabilities in estimating cointegration relationships in time series, as explained below. The software used for all econometric calculations is EViews version 12, selected for its high efficiency in time-series analysis and advanced diagnostic testing tools.

In general, the research variables are defined as shown in Table 4.

Table 1. Variable Specifications

Variable Name	Symbol	Role in Model	Data Source
Number of Branches	$\boldsymbol{Bra}$	Dependent	World Bank Data
Digital Banking	$\boldsymbol{DB}$	Independent	Statista
Digital Payments	$\boldsymbol{DP}$	Independent	Statista
Liquidity	$\boldsymbol{LIQ}$	Control	Federal Reserve Economic Data (FRED)

Source: Research Findings

The general model of the research is defined as Equation 1:

$$Bra_t = \alpha_0 + \beta_1 BD_t + \beta_2 PD_t + \beta_3 LIQ_t + \varepsilon_t \tag{1}$$

By enabling the simultaneous estimation of short-term and long-term relationships among variables, the ARDL model offers significant methodological advantages over traditional cointegration approaches. On one hand, it possesses high flexibility regarding the order of integration of the variables; it can simultaneously estimate variables that are stationary at level $I(0)$ and stationary at the first difference $I(1)$ within a single equation—without requiring them to be of the same order (provided none are $I(2)$). On the other hand, it demonstrates high robustness and efficiency in analyzing small to medium-sized samples, which significantly enhances the reliability and validity of the results derived from the 22 time-series observations in this study.

2.5. Methodological Limitations

Every methodology in time-series-based econometric studies faces inherent limitations, the clarification of which aids in a better understanding of the results. In the present study, the first challenge relates to the limited time scope and the high sensitivity of data to historical shocks and structural changes, as the accelerating growth of technology in recent years may necessitate diagnostic tools for structural breaks. The second limitation is rooted in the difficulty of operationally defining multi-faceted variables such as “digital banking,” as existing composite indices may not capture all the subtle dimensions of artificial intelligence, thereby increasing the risk of omitted variable bias. Furthermore, the analysis heavily depends on the quality and consistency of secondary data obtained from international authorities, as well as the challenge of accessing standardized statistics for emerging technologies in the early years of the period. Finally, the inductive and statistical nature of econometric models does not, in itself, prove definitive real-world causality, although the use of the cointegration approach in the ARDL model significantly contributes to strengthening the stability and directionality of these relationships in the long term.

3. Results and *Discussion*

This section presents and interprets the results obtained from the analysis of annual data for the period 2004 to 2025 using EViews version 12 software. The main objective of the analysis is to examine how the development of digital banking, the expansion of digital payments, and the liquidity situation affect the number of physical bank branches. Given the time-series nature of the data and the possibility that the variables may have different orders of stationarity, the Autoregressive Distributed Lag model was used. It should be noted that the figures inside brackets and tables in this section must be completed using the actual EViews software output after entering the data so that the findings can be finally cited. In this regard, an analysis of the trend in the number of branches in Figure 1 is first presented.

Figure 12. Trend in the Number of Branches

Source: Research Findings

According to Figure 13, the trend in the number of branches during the period 2004 to 2025 indicates that the physical structure of the banking network experienced considerable fluctuations over this period. The number of branches followed an upward trend from 2004 to approximately 2007 and was then accompanied by a gradual decline until 2010. After that, relatively sharp growth was observed in 2011 and 2012, which constituted the peak of the period under study. However, from 2013 onward, although limited and temporary increases occurred in some years, the overall path of the number of branches was predominantly downward. The noticeable decline in the indicator between 2017 and 2020 and it’s reaching the minimum level of the period may reflect the increased adoption of digital banking, the development of non-face-to-face payments, the decline in customer visits to branches, and banks’ reassessment of the operating costs of their physical networks. The temporary increase in the number of branches in 2021 and the limited fluctuations in subsequent years also indicate that the transition to digital banking has not necessarily led to the complete elimination of branches; rather, it has resulted in changes in their functions, geographical restructuring, and a focus of the remaining branches on more specialized and value-creating services. Overall, the figure indicates the gradual movement of the banking system toward a digital service delivery model and a relative reduction in dependence on traditional branches.

3.1 Descriptive Statistics

Descriptive statistics provide an initial picture of the status, dispersion, and behavior of the research variables during the period under study. The dependent variable of the research is the number of physical bank branches, while the explanatory variables include the digital banking index, the volume or value of digital payments, and the liquidity index. Examining these indicators before proceeding to the econometric stages is necessary because severe dispersion, outliers, or unusual distributions may affect the estimation of coefficients and the reliability of the results.

Table 2. Descriptive Statistics of the Model

Statistic	Bra	DB	DP	LIQ
Mean	11.47342	169.2995	3.286803	5.152965
Median	11.36773	13.37000	3.236110	5.148842
Maximum	12.65874	956.2300	4.133060	5.420878
Minimum	10.01460	0.190000	2.432969	4.8767715
Standard Deviation	0.784144	290.5723	0.553113	0.182919
Skewness	-0.058915	1.683817	0.076178	0.111151
Kurtosis	1.769274	4.463159	1.694046	1.741446
Jarque-Bera Statistic	1.404489	12.35831	1.584667	1.497262
Observations	22	22	22	22

Source: Research Findings

According to Table 5, the number of observations for all research variables is equal to 22 observations, covering the period from 2004 to 2025. The mean number of branches is 11.47342 and its median is 11.36773. The proximity of these two indicators shows that the distribution of the number of branches during the study period does not exhibit unusual dispersion, although its negative skewness value of -0.058915 indicates a very slight tendency of the distribution toward lower values. The number of branches in this period has a minimum of 10.01460 and a maximum of 12.65874, while the standard deviation of 0.784144 indicates moderate fluctuations in this variable. The mean value of digital banking is 169.2995 and its median is 13.37000. The considerable gap between these two indicators, together with the positive skewness of 1.683817, indicates unbalanced growth and the concentration of observations at lower levels during a significant part of the period. In other words, the development of digital banking has accelerated in the final years. This variable also exhibits the highest dispersion among the model variables, with a standard deviation of 290.5723, which may result from the rapid expansion of infrastructure and the increasing adoption of digital services. The mean value of digital payments is reported as 3.286803 and its median as 3.236110. The proximity of these two values, along with the slight positive skewness of 0.076178, indicates that the distribution of this variable is relatively symmetrical. The range of changes in digital payments extends from 2.432969 to 4.133060, and its standard deviation is 0.553113, indicating controllable but meaningful fluctuations in this indicator over time. Furthermore, the mean liquidity is 5.152965 and its median is 5.148842, while its minimum and maximum are reported as 4.8767715 and 5.420878, respectively. Given the positive skewness of 0.111151, the liquidity distribution is almost symmetrical, and its standard deviation of 0.182919 also indicates limited fluctuations. In terms of kurtosis, the value of this indicator for the number of branches, digital payments, and liquidity is less than three, indicating a distribution relatively flatter than the normal distribution. In contrast, the kurtosis value of digital banking, equal to 4.463159, indicates a greater concentration of data and the presence of relatively prominent values in this variable. Overall, the descriptive statistics indicate that the number of branches and liquidity have relatively greater stability, whereas digital banking and digital payments, particularly digital banking, have experienced greater variability and transformation during the period under study. The Jarque-Bera statistics for the number of branches, digital banking, digital payments, and liquidity are 1.404489, 12.35831, 1.584667, and 1.497262, respectively. However, a definitive judgment regarding the normality of the distribution of each variable requires examination of the probability values corresponding to these statistics.

3.2. Unit Root Test

Before estimating the Autoregressive Distributed Lag model, it is necessary to determine the order of stationarity of the research variables. The use of non-stationary time series at level may lead to spurious regression, meaning that a statistically significant relationship may be observed among variables even though such a relationship is not economically real or stable. To prevent this issue, the Augmented Dickey-Fuller unit root test and, where necessary, the Phillips-Perron test was performed. The null hypothesis in the unit root test indicates the existence of a unit root and the non-stationarity of the time series, whereas the alternative hypothesis indicates that the variable is stationary. An important feature of the Autoregressive Distributed Lag approach is that it allows the simultaneous use of variables that are stationary at level and variables that become stationary after first differencing. However, the presence of a variable that is stationary only after second differencing makes the use of this approach inappropriate.

Table 3. Augmented Dickey-Fuller Unit Root Test

Variable	Level $I(0)$		First Difference $I(1)$	
	T-Statistic	P-Value	T-Statistic	P-Value
Bra	-2.378029	0.1593	-5.169132	0.0005
DB	-1.003694	0.7285	-7.970143	0.0000
DP	-0.214247	0.9224	-3.586768	0.0159
LIQ	-0.400282	0.8922	-3.615274	0.0150

Source: Research Findings

Table 6 shows that none of the model variables, including the number of branches, digital banking, digital payments, and liquidity, are stationary at their initial levels because the probability value of the Augmented Dickey-Fuller test for all variables is greater than the five percent significance level. Specifically, the probability values for the number of branches, digital banking, digital payments, and liquidity are 0.1593, 0.7285, 0.9224, and 0.8922, respectively. Therefore, the null hypothesis of the existence of a unit root at level is not rejected for all variables. However, after first differencing, the test statistics for the number of branches, digital banking, digital payments, and liquidity reach -5.169132, -7.970143, -3.586768, and -3.615274, respectively, while the corresponding probability values become 0.0005, 0.0000, 0.0159, and 0.0150, respectively. Since all these probability values are below five percent, the null hypothesis of a unit root in the first difference is rejected, and the hypothesis of variable stationarity is accepted. Accordingly, all research variables are integrated of order one, meaning that they become stationary after one differencing. This finding is methodologically important because none of the variables become stationary only after second differencing. Therefore, the use of the Autoregressive Distributed Lag model to investigate the short-run and long-run relationship among digital transformation, digital payments, liquidity, and the number of bank branches is statistically justifiable.

3.3. Granger Causality Test

The Granger causality test is used to examine the temporal precedence and predictive power of variables relative to one another. In this test, causality does not necessarily refer to a definite and philosophical cause-and-effect relationship; rather, it determines whether the past information of one variable significantly improves the prediction of another variable. In this study, the Granger causality test is performed to investigate the relationships among the number of branches, digital banking, digital payments, and liquidity.

Table 4. Granger Causality Test

Dependent Variable	Omitted Variable	Chi-square Statistic	df	Probability
$\boldsymbol{Bra}$	Digital Banking	265486.2	2	0.3221
	Digital Payments	324131.3	2	0.1897
	Liquidity	445136.1	2	0.4855
	All Variables	879798.7	6	0.2470
$\boldsymbol{DB}$	Branch Count	687970.3	2	0.1582
	Digital Payments	857631.4	2	0.0881
	Liquidity	590768.4	2	0.1007
	All Variables	53534.11	6	0.0732
$\boldsymbol{DP}$	Branch Count	323838.1	2	0.5159
	Digital Banking	45114.10	2	0.0054
	Liquidity	921362.1	2	0.3826
	All Variables	55149.14	6	0.0240
$\boldsymbol{LIQ}$	Branch Count	410697.2	2	0.2996
	Digital Banking	65874.13	2	0.0011
	Digital Payments	248943.6	2	0.0440
	All Variables	12761.34	6	0.0000

Source: Research Findings

Table 7 shows that the causality pattern among the research variables is unidirectional and asymmetric, and not all variables affect one another to the same extent. In the equation related to the number of branches, none of the digital banking, digital payments, and liquidity variables are significant at the five percent level. Therefore, there is no evidence of direct Granger causality toward the number of branches. Likewise, in the case of digital banking, none of the explanatory variables, including the joint test of all variables, reaches the significance level. This indicates that changes in this variable are more influenced by internal mechanisms and factors beyond the variables included in the model. In contrast, in the digital payment's equation, digital banking has a significant causal effect, with a Chi-square statistic of 10.451 and a probability value of 0.0054. The joint test is also significant at the five percent level. This result indicates that the development of digital banking is an important predictor of transformation in digital payments. Furthermore, in the liquidity equation, both digital banking and digital payments have significant causal effects, and the joint test is also confirmed with a probability close to zero. Therefore, it can be concluded that the digitization of banking services affects not only payment behavior but is also associated with changes in the liquidity situation at a broader level. Overall, the findings indicate that the direction of causality mainly flows from digital banking toward digital payments and liquidity, while the number of branches is not affected by these variables within the Granger causality framework of this model.

3.4. Optimal Lag Test

Determining the appropriate number of lags is one of the fundamental stages in time-series analysis. Selecting a very short lag may overlook the actual dynamics of the variables and result in the persistence of autocorrelation in the error terms. On the other hand, selecting excessive lags, particularly given the limited number of observations, reduces the degrees of freedom and weakens the precision of the estimates. The Akaike, Schwarz Bayesian, Hannan-Quinn, and likelihood ratio criteria are used to select the optimal lag. Given the relatively limited sample size, the Schwarz Bayesian criterion is considered more appropriate for selecting the final model because it imposes a greater penalty for the addition of unnecessary lags.

Table 5. Optimal Lag Selection Test

Lag Length	Akaike	Schwarz	Hannan-Quinn
0	11.82281	12.02177	11.86599
1	0.931038*	1.925821*	1.146931*

Source: Research Findings
Note: The asterisk (*) indicates the optimal lag.

Table 8 shows that, based on all three information criteria—Akaike, Schwarz, and Hannan-Quinn—the first lag is selected as the optimal lag of the model. Specifically, the Akaike criterion value at lag zero is 11.82281, which decreases to 0.931038 at the first lag. Similarly, the Schwarz criterion decreases from 12.02177 at lag zero to 1.925821 at the first lag, and the Hannan-Quinn criterion declines from 11.86599 to 1.146931. Since a lower value in information criteria indicates a better model fit while avoiding an unnecessary increase in complexity, the convergence of the results of the three criteria on the first lag strengthens the validity of the selection made. The selection of one lag indicates that current changes in the number of bank branches and variables related to digital transformation, digital payments, and liquidity are primarily influenced by their values in the previous period. Adding more lags does not produce a significant improvement in the explanatory power of the model. Therefore, the dynamic research model with one lag, while preserving the temporal structure of the relationships among variables, prevents a reduction in degrees of freedom and overfitting and provides an appropriate basis for estimating the Autoregressive Distributed Lag model and testing short-run and long-run relationships.

3.5. Model Estimation

After confirming the stationarity of the variables at level or first difference and selecting the appropriate lag structure, the Autoregressive Distributed Lag model is estimated. In this model, the logarithm of the number of physical bank branches is included as the dependent variable, while the logarithm of the digital banking index, the logarithm of digital payments, and the logarithm of liquidity are included as explanatory variables. In addition to moderating data dispersion and reducing the likelihood of heteroskedasticity, the use of the natural logarithm makes it possible to interpret the coefficients as elasticities.

The general form of the long-run relationship in the research is such that percentage changes in digital banking, digital payments, and liquidity may be associated with percentage changes in the number of branches. The theoretical expectation is that the coefficients of digital banking and digital payments will be negative in the long run because increased use of digital channels reduces dependence on in-person services and branch visits. Nevertheless, the sign and significance of the coefficients should be interpreted solely on the basis of the estimated results in EViews.

Table 6. ARDL (2,4,3,4) Model Estimation Results

Variable	Coefficient	Standard Error	T-Statistic	Significance Level
$\boldsymbol{Bra(-2)}$	-0.946217	0.080118	-11.81030	0.0071
$\boldsymbol{DB(-1)}$	-0.319367	0.036200	-8.822327	0.0126
$\boldsymbol{DP(-1)}$	-35.37130	2.664125	-13.27689	0.0056
$\boldsymbol{LIQ(-1)}$	-44.71976	3.956051	-11.30414	0.0077

Model Statistic	Value	Information Criterion	Value
R-squared	0.999571	Akaike	-3.773166
Adjusted R-squared	0.996354	Schwarz	-2.981725
Durbin-Watson	3.561956	Hannan-Quinn	-3.664037

Source: Research Findings

Table 9 presents the estimation of the Autoregressive Distributed Lag model with a lag structure of two, four, three, and four, indicating the existence of a negative and significant relationship between the number of bank branches and the lagged values of the model variables. The coefficient of the second lag of the number of branches is -0.946217 and is significant at a level below one percent. This result indicates that changes in the number of branches in previous periods have a considerable moderating and reducing effect on the number of branches in the current period, and the adjustment dynamics in the structure of bank branches occur with high intensity. Digital banking, with a negative coefficient of -0.319367 and a significance level of 0.0126, has a negative and significant effect on the number of branches. Therefore, the expansion of the use of digital banking infrastructure and services is associated with a reduced need for customers' physical presence and a decline in banks' reliance on branch networks. Digital payments also demonstrate a negative and significant effect on the number of branches, with a coefficient of -35.37130 and a significance level of 0.0056. The relative magnitude of this coefficient suggests that the development of non-face-to-face payment instruments has resulted in the transfer of part of transactions from branches to electronic channels and a reduction in the operational functions of branches. Moreover, liquidity, with a negative coefficient of -44.71976 and a significance level of 0.0077, has a negative and significant effect on the number of branches. This may reflect banks' tendency to manage fixed costs, optimize resource allocation, and reconsider the geographical distribution of branches under changing liquidity conditions. The R-squared value of 0.999571 and the adjusted R-squared value of 0.996354 indicate that the model explains a very large proportion of changes in the number of branches. However, given the limited sample size and the number of lags included in the model, these indicators should be interpreted with caution. The Durbin-Watson statistic is 3.561956, which may indicate negative autocorrelation in the residuals. Overall, the model findings support the view that the expansion of digital banking and digital payments, together with liquidity developments, is associated with a reduction in the number of bank branches and reinforces the movement of banks toward lower-cost, less in-person, and digitally oriented structures.

4. Conclusions

The transformation of the traditional structure of the banking industry and the transition toward modern operational models are inevitable phenomena driven by the accelerating adoption of digital technologies. The findings of this research, based on the analysis of a 22-year trend, indicate that the number of physical bank branches, after experiencing a period of growth and reaching its peak during 2011 to 2012, has followed a declining path. This downward trend reached its lowest point particularly during 2017 to 2020, which is closely correlated with the first wave of widespread adoption of digital banking and non-face-to-face systems. Although the fluctuations in the subsequent years indicate the survival of part of the physical core for the provision of specialized and complex services, the overall market direction demonstrates a shift in the role of branches from primary centers for recording daily transactions to hubs of specialized consultation and value creation.

The results of the stationarity and Augmented Dickey-Fuller unit root tests confirmed that all key model variables, including the number of branches, the digital banking index, digital payments, and liquidity, were non-stationary at level and became stationary after first differencing. This characteristic confirms the validity of using the Autoregressive Distributed Lag model. In this regard, the Granger causality test provides a clear picture of the internal dynamics of these variables. Based on this test, a strong and unidirectional causal path exists from the development of digital banking infrastructure toward the volume of non-face-to-face payments and changes in liquidity. This finding means that policymaking in the field of banking technologies and digitalization, as a primary driving force, transforms customers' transactional behavior and the liquidity structure and indirectly provides the necessary foundation for optimizing the physical network.

The final estimation of the Autoregressive Distributed Lag model with the optimal dynamic structure revealed the negative, significant, and stable effects of digital and monetary variables on the survival of physical branches. The negative coefficient of digital banking indicates that the enhancement of virtual infrastructure continuously reduces the need for physical presence. This reducing effect is reflected with much greater intensity in the digital payment's variable, indicating the transfer of a massive volume of small and medium-sized transactions from branch counters to electronic and mobile gateways. Moreover, the negative and significant coefficient of liquidity reflects the structural response of banks in managing fixed costs and optimizing physical branches in response to macroeconomic developments. Overall, the high explanatory power of the estimated model confirms that a major part of the changes toward reducing physical branches results from digital transformation and changing payment patterns.

Considering global forecasts regarding the rapid annual growth of the artificial intelligence market in the financial sector and the substantial expansion of the neobank market value by 2033, the future of the banking industry will be shaped around branch lessness and maximum service personalization. Global crises have proven to be strong accelerators, demonstrating that the sustainability of financial services is ensured through smart tools. Generative artificial intelligence, blockchain technology, and smart contracts are tools that not only increase efficiency and speed but also attract public trust toward decentralized structures by improving cybersecurity and reducing human errors. Therefore, financial organizations around the world are compelled to redesign their business models and make targeted investments in these emerging technologies in order to maintain their competitive survival.

In order to adapt efficiently to these structural transformations, banks should adopt coherent strategic measures. This path begins with investment in big-data infrastructure and cloud computing for the rapid processing of information and becomes more profound through the implementation of artificial intelligence tools such as responsive chatbots, intelligent fraud detection systems, and the automation of internal processes. Establishing dedicated neobanks and developing comprehensive financial-service applications, alongside active partnerships with fintech companies and innovative start-ups, will enhance banks' competitive capabilities. At the same time, empowering human capital through training in new information-technology skills, improving cybersecurity, and conducting continuous penetration testing to protect user privacy are of vital importance. Finally, using blockchain platforms for secure money transfers and smart-contract arrangements, together with improving the transparency of financial reporting, will provide the foundation for attracting stakeholder trust in the fully digital banking ecosystem.

Author Contributions

The author was solely responsible for the conception, preparation, and writing of this manuscript.

Conflict of Interest

The author, while observing publication ethics in the referencing, declares the absence of any conflict of interest.

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