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ORIGINAL RESEARCH PAPER

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

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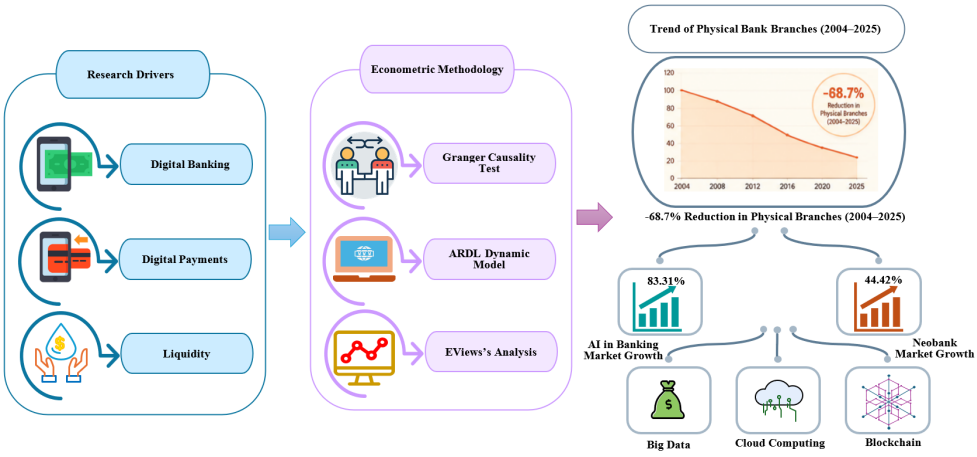
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*A B S T R A C T*

This study examines the relationships between digital banking, digital payments, liquidity conditions, and the number of physical bank branches over 2004–2025, and discusses how these changes may support a greener digital banking transition. The empirical analysis uses an autoregressive distributed lag (ARDL) model estimated in EViews 12. Augmented Dickey–Fuller results indicate that the variables are non-stationary at level and stationary after first differencing. Granger tests identify unidirectional predictive relationships from digital banking to digital payments and liquidity. The reported dynamic-model estimates associate digital banking, digital payments, and liquidity with fewer physical branches, with coefficients of −0.319, −35.37, and −44.71, respectively. These results are consistent with a shift toward remote service delivery, but do not directly measure carbon emissions, energy use, paper consumption, e-waste, or other environmental outcomes. Accordingly, the paper treats environmental benefits as potential, conditional co-benefits—not as findings established by the econometric model. A green digital strategy should combine responsible branch-network optimization with energy-efficient data centers, renewable electricity where feasible, durable and repairable devices, responsible e-waste management, strong cybersecurity, and inclusive access. Banks should measure lifecycle impacts alongside service quality and financial inclusion before claiming net environmental gains.




## 1. Introduction

Rapid technological change is reshaping banking operations and the ways customers access financial services. Banks face continuing pressure to improve efficiency, manage costs, and provide reliable services. Artificial intelligence (AI), cloud computing, data analytics, and mobile platforms can support this transformation by automating selected processes and enabling more remote service delivery [1]. A green digital transformation, however, requires more than digitization: it also considers the energy and material footprint of digital infrastructure, the environmental consequences of physical facilities and devices, and equitable access to services.

Banking services that once depended heavily on in-person branch visits are increasingly available through online and mobile channels. This shift accelerated during and after the COVID-19 pandemic as demand for remote services increased [2]. Digital channels may reduce customer travel and some paper-intensive transactions, while branch consolidation may reduce building-related resource use. These potential benefits depend on actual changes in travel, building operations, and paper use, and must be weighed against the electricity, equipment, and data-center demands of digital services.

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AI capabilities—including large-scale data analytics, natural-language processing, machine learning, and conversational systems—can help banks automate workflows, improve decision support, and tailor customer services [3,4]. For a green digital organization, these tools may also support energy and resource management, such as monitoring facility use or identifying inefficient processes. Such environmental applications require appropriate data, governance, and outcome measurement; they cannot be inferred from AI adoption alone.

This study examines the association of digital banking, digital payments, and liquidity with the number of physical bank branches over 2004–2025, and interprets the findings in the context of a possible transition toward green digital banking. It does not estimate environmental impacts or forecast outcomes for 2030–2034. The discussion therefore distinguishes the study's measured banking outcomes from proposed sustainability implications and identifies environmental indicators that future research should test directly.

AI can support banking operations through data analysis, fraud-risk detection, customer onboarding, document processing, and automated customer interaction [5]. It is also used in customer service, fraud detection, and investment management [6]. The pandemic accelerated remote service adoption and broader use of digital tools [7,8]. From a sustainability perspective, automation and remote transactions could reduce some resource-intensive activities, but the net effect depends on the energy mix, the scale and efficiency of computing, device lifecycles, customer travel, and rebound effects. This study does not quantify those factors.

Green-digital banking should be understood as a dual transformation: expanding accessible, secure digital services while managing the environmental footprint of both physical operations and digital infrastructure. Potential gains—such as reduced paper use, fewer customer journeys, or more efficient buildings—are conditional and may be offset by data-center electricity demand, device production and replacement, or rebound effects. These outcomes should be evaluated with measured, lifecycle-informed indicators rather than assumed from branch closures.

The application of blockchain-based AI in the banking industry, as seen in Figure 1, 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 [9].

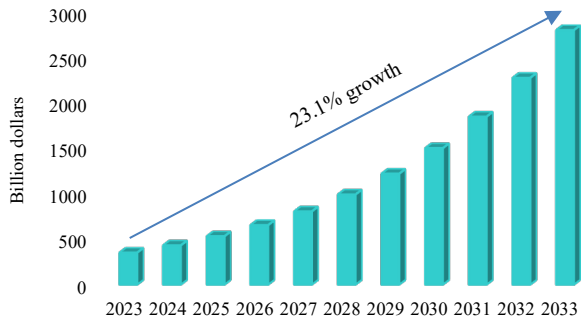



**Figure 1.** Forecasted Global Market Value of Blockchain-Based AI in Banking and Financial Services (2022–2030)

Source: Ref [9]

Figure 2 illustrates that 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 [10].

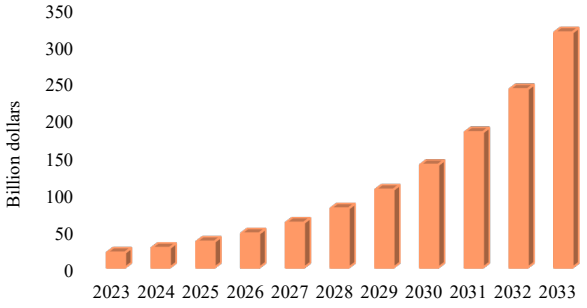



**Figure 2.** Forecasted Global AI Market Size in Banking and Financial Services (2023–2033)

Source: Ref [10]

According to Figure 3, 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 [11].

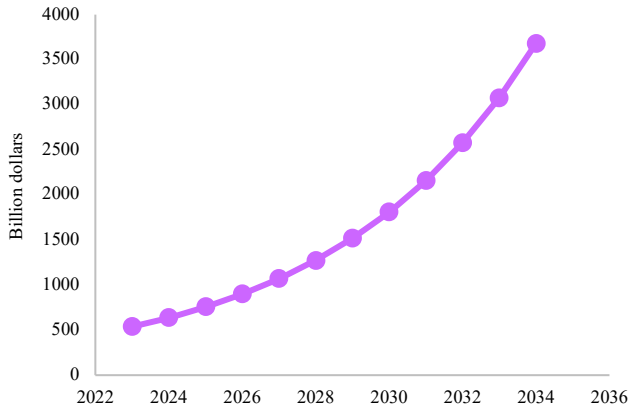



**Figure 3.** Forecasted Global AI Market Growth Size (2023–2034)

Source: Ref [11]

Figure 4 shows that 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 [12].

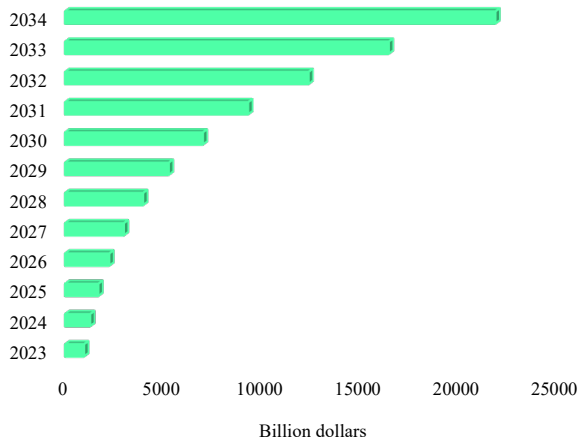



**Figure 4.** Forecasted Global Generative AI Market Size in B anking and Financial Services (2023–2034)

Source: Ref [12]

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 [13,14].

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 [15]. 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 [16,17]. Furthermore, ML is widely utilized in banking for credit risk assessment and prediction, fraud detection via real-time transaction pattern analysis, and personalized marketing [18]. 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% [19].

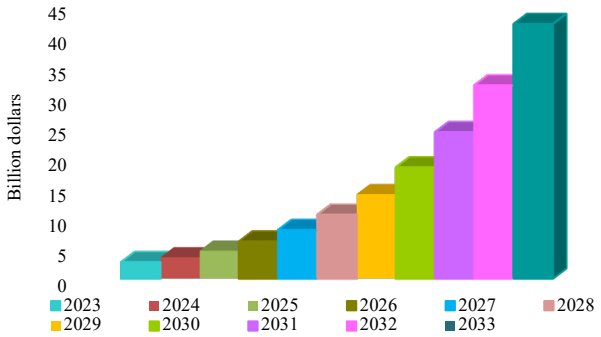



**Figure 5.** Forecasted Global Machine Learning Market Size in Financial Services (2022–2032)

Source: Ref [19]

According to Figure 6, 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 [20].

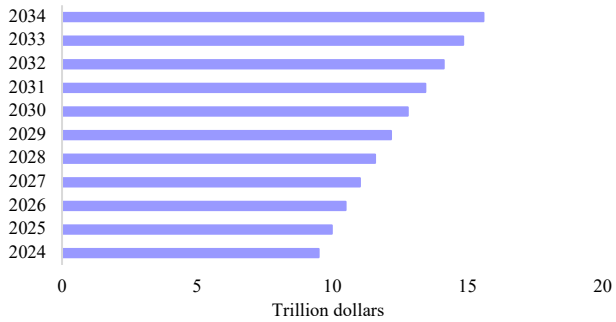



**Figure 6.** Global E-Banking Market Size (2024–2034)

Source: Ref [20]

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 2023–2033 period. The Asia-Pacific region dominated the market in 2023 with a 36.5% share and revenue generation of $5.47 billion [21].

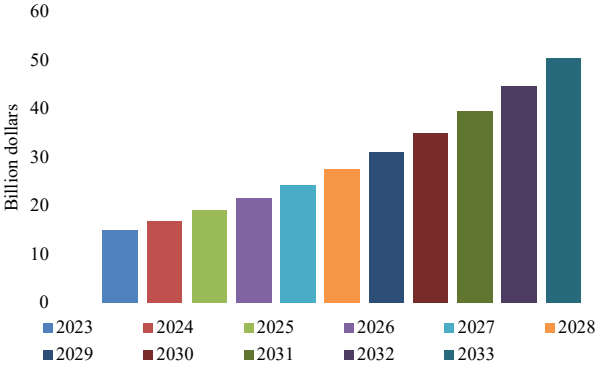



**Figure 7.** Global Digital Banking Platforms and Services Market (2023–2033)

Source: Ref [21]

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 7 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.

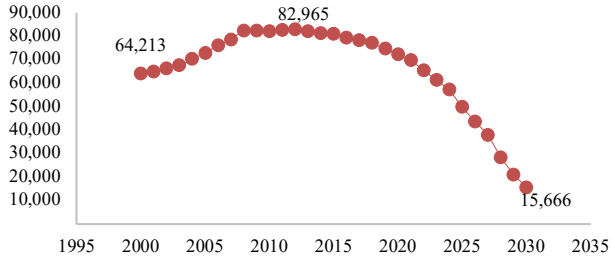



**Figure 8.** Forecast of US Bank Branch Counts (2000–2030)

Source: Ref [22]

With the advancement of technologies such as AI and blockchain, some banking services are increasingly delivered by branchless neobanks. Neobanks provide services through online platforms and may avoid certain costs associated with maintaining extensive branch networks. Their growth does not establish that physical branches will disappear by a particular year; branch needs vary with regulation, customer needs, geography, and access requirements. A green assessment must also account for the environmental footprint of digital infrastructure and devices, rather than equating branch reduction automatically with environmental improvement.

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 [23].

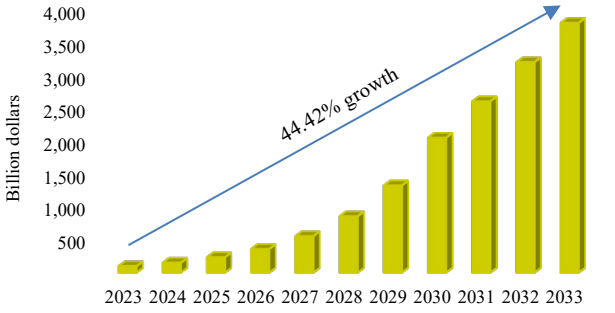



**Figure 9.** Forecasted Global Neobank Market Size and Growth (2023–2033)

Source: Ref [23]

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 [23].

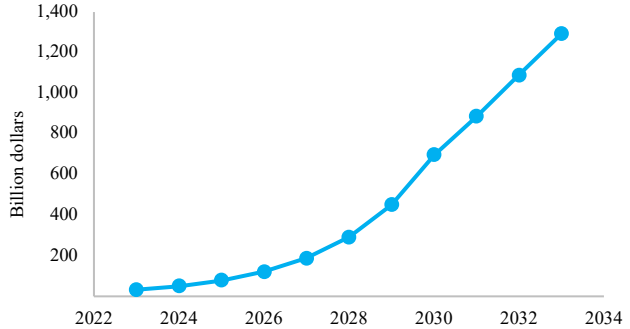



**Figure 10.** Forecasted Neobank Market Size and Growth in Europe (2023–2033)

Source: Ref [23]

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 [23].

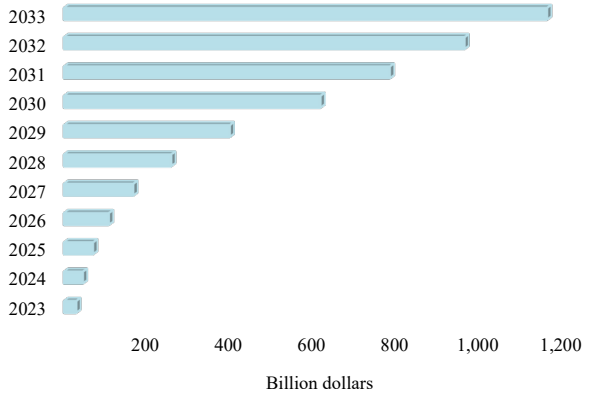



**Figure 11.** Forecasted Neobank Market Size and Growth in North America (2023–2033)

Source: Ref [23]

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.

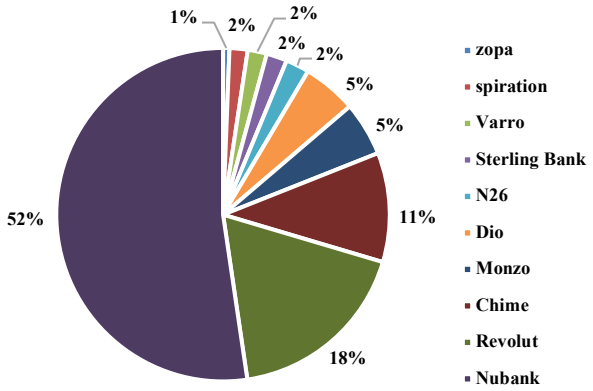



**Figure 12.** User Count of the Top 10 Neobanks in the World in 2025 (Millions of Users)

Source:Refs [24-30]

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: Refs [24-30]

User metrics suggest that neobanks can serve large customer bases without expanding conventional branch infrastructure, illustrating a shift toward platform-based banking. AI applications reported in this context include customer behavior analysis, personalized recommendations, rapid credit assessment, fraud detection, risk management, and automated support. These practices may improve operational efficiency, but user growth and reduced branch dependence are not, by themselves, evidence of lower lifecycle environmental impact.

- 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 may reduce selected operating costs and service times and improve customer experience. Whether they also reduce environmental burdens is an empirical question requiring measures such as energy consumption, emissions, paper use, equipment turnover, and e-waste.

Comparative observations suggest that AI-enabled data analytics, process automation, and digital services can accompany a declining role for routine in-person branch activity. The association should not be interpreted as proof that AI alone causes branch closures or that closures necessarily deliver net environmental gains.

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

In neobanks, service delivery may be largely branchless; in traditional banks, digitalization can instead change branch functions. AI therefore need not immediately eliminate branches: it may support a shift toward advisory or complex-service locations. In a green digital transition, decisions about branch use should consider building energy performance, customer travel and access, local service needs, and the environmental costs of digital alternatives.

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) [31].

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) [32-45].

**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: [32-45]

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 suggests that a key difference between Iranian banks and global digital-banking trends concerns the maturity of AI, data-driven decision-making, and digital-first service architecture. The comparison does not evaluate environmental performance. Future assessment should examine whether Iranian banks can integrate sustainability measurement—such as facility energy use, data-center efficiency, paper consumption, device procurement, and e-waste management—into digital transformation while maintaining inclusion and service resilience.

**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 material reviewed indicates that global banking is moving toward more digital, data-driven service models, while Iranian banks have expanded mobile applications and remote services but remain in transition. This comparison highlights differences in digital and AI maturity, not a measured difference in environmental impact. To move toward green digital organization, banks in Iran and elsewhere can pair service redesign and responsible AI with environmental accounting, energy-efficient infrastructure, renewable-energy procurement where feasible, circular device practices, and accessible alternatives for customers who rely on in-person services. The net sustainability outcome should be verified using consistent operational and lifecycle indicators.

## 2. Method

The methodology sets out the analytical framework used to examine the relationship between digital transformation—represented by digital banking and digital payments—and the physical structure of banks, measured by the number of branches. Environmental performance is discussed as a strategic implication but is not a dependent or explanatory variable in the empirical model.

### *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 [46].
- 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 [47].
- 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 [48-52].

The collected data were organized as annual time series and checked for consistency. The dataset described in this study does not include direct environmental indicators; consequently, the analysis cannot estimate emissions, energy savings, paper reduction, or lifecycle impacts attributable to digitalization or branch changes.

### *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 | $Bra$ | Dependent | World Bank Data |
| Digital Banking | $DB$ | Independent | Statista |
| Digital Payments | $DP$ | Independent | Statista |
| Liquidity | $LIQ$ | Control | Federal Reserve Economic Data (FRED) |

Source: Research Findings

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

$$Bra_t = \alpha_0 + \beta_1 BD_t + \beta_2 PD_t + \beta_3 LIQ_t + \varepsilon_t \quad (1)$$

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*

This time-series analysis has important limitations. The sample covers 2004–2025 and may be sensitive to structural breaks and historical shocks. Composite measures such as digital banking may not capture the maturity or specific applications of AI, creating a risk of omitted-variable bias. The analysis depends on the quality and consistency of secondary data, and the small sample constrains model complexity. ARDL and Granger procedures identify statistical relationships and predictive precedence, not definitive real-world causation. Most importantly for the green-digital framing, the model contains no direct environmental variables—such as operational emissions, electricity use, building energy, customer travel, paper use, or e-waste—and therefore cannot establish that digitalization or branch reduction improved environmental performance. Future studies should add these measures, specify boundaries and time horizons, and test lifecycle and rebound effects.

## 3. Results and *Discussion*

This section reports the analysis of annual data for 2004–2025 using EViews 12. The empirical objective is to examine how digital banking, digital payments, and liquidity relate to the number of physical bank branches. Given the time-series properties of the variables, an ARDL approach is applied. Environmental sustainability is not directly modeled; the green implications below are therefore cautious interpretations and recommendations, not estimated environmental effects. Any incomplete figures or tables must be verified against the underlying data and actual EViews output before publication.




**Figure 13.** Trend in the Number of Branches

Source: Research Findings

The branch-count series fluctuates over the study period, rising to a peak around 2011–2012 and generally declining after 2013, with a marked decrease during 2017–2020 and some later variation. This pattern is consistent with a gradual reconfiguration of branch networks and the expansion of remote services, but it does not by itself identify the cause of change. From a green-digital perspective, fewer branches could reduce building-related resource use if facilities are closed or used more efficiently; however, customer travel, replacement service infrastructure, data-center electricity, and digital-device impacts could offset some gains. Since these factors are not measured here, no net environmental effect can be concluded.

### *3.1 .Descriptive Statistics*

Descriptive statistics provide an initial view of the research variables over the study period. The dependent variable is the number of physical bank branches; the explanatory variables are the digital banking index, digital payments, and liquidity. These statistics help assess variation and potential outliers before econometric estimation. No environmental-performance variable is included, so this step does not describe banks' green outcomes.

**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 |
|---|---|---|---|---|
| $Bra$ | 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 |
| $DB$ | 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 |
| $DP$ | 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 |
| $LIQ$ | 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 long-run model relates percentage changes in digital banking, digital payments, and liquidity to percentage changes in the number of branches. A negative association between digital banking or digital payments and branch numbers is theoretically plausible where remote channels substitute for in-person transactions, but signs and significance must be determined from verified estimates. Such a relationship would not, on its own, demonstrate environmental improvement; environmental hypotheses require separate outcome measures and appropriate controls.

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

| Variable | Coefficient | Standard Error | T-Statistic | Significance Level |
|---|---|---|---|---|
| $Bra(-2)$ | -0.946217 | 0.080118 | -11.81030 | 0.0071 |
| $DB(-1)$ | -0.319367 | 0.036200 | -8.822327 | 0.0126 |
| $DP(-1)$ | -35.37130 | 2.664125 | -13.27689 | 0.0056 |
| $LIQ(-1)$ | -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

The reported ARDL estimates show negative and statistically significant coefficients for digital banking (−0.319367; p=0.0126), digital payments (−35.37130; p=0.0056), and liquidity (−44.71976; p=0.0077) in relation to the number of branches. These estimates are consistent with an association between the included variables and a smaller branch network, but their interpretation depends on the model specification, variable transformations, sample size, and verification of the reported EViews output. The high R-squared (0.999571) should be treated cautiously given the 22 observations and many lags; the Durbin–Watson statistic (3.561956) also warrants diagnostic follow-up. The model does not include environmental outcomes, so it cannot show that these branch-related associations reduce emissions or resource use. Green-digital implications remain hypotheses to be evaluated with additional data.

## 4. Conclusions

This study considers the transition from branch-centered banking to digital service delivery using annual data for 2004–2025. The branch series is reported to peak around 2011–2012 and generally decline thereafter, with a low during 2017–2020 and later fluctuations. This trajectory is consistent with a changing role for branches, which may increasingly focus on advice and complex services rather than routine transactions. Whether this restructuring is environmentally beneficial depends on facility energy use, customer travel, digital infrastructure, and other lifecycle effects that were not measured in this study.

The unit-root results reported in the paper indicate that the model variables are non-stationary at level and stationary after first differencing, supporting consideration of an ARDL framework, subject to standard specification checks. Granger results identify predictive relationships from digital banking to digital payments and liquidity, but do not establish definitive causation. These findings can inform hypotheses about how digital service development relates to branch optimization; they do not establish environmental benefits.

The reported ARDL results associate digital banking, digital payments, and liquidity with fewer physical branches. These findings support further evaluation of how banks can provide services efficiently as customer activity shifts to digital channels. However, high model fit should be interpreted in light of the short sample, extensive lag structure, and residual diagnostics. Because the model does not include energy, emissions, travel, paper, or lifecycle data, it cannot attribute any environmental improvement to digital transformation or branch reduction.

The expansion of AI and neobanking may reshape financial services, but growth forecasts are not evidence of sustainability performance. AI, cloud computing, blockchain, and automated services can enable new operating models while also requiring electricity, computing equipment, and robust cybersecurity. A green digital organization should assess both sides of this transition, set measurable environmental targets, and avoid treating branchlessness or technology adoption as a proxy for decarbonization.

Banks seeking a responsible green digital transition should: (1) invest in efficient data infrastructure and measure its energy and emissions footprint; (2) use AI for transparent, governed applications, including where appropriate the monitoring of operational resource use; (3) evaluate branch changes alongside customer access, travel, building efficiency, and community needs; (4) procure durable, repairable devices and establish responsible reuse and e-waste programs; (5) strengthen cybersecurity, privacy, and human oversight; and (6) publish comparable indicators on service quality, financial inclusion, resource use, and emissions. Partnerships with fintechs and staff training can support implementation, but claims of environmental benefit should be based on measured outcomes and lifecycle boundaries.

## 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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## Data availability

This article does not contain any Supplementary Material.

## AI Use Statement

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