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THE IMPACT OF INDUSTRY 4.0 ON EMPLOYMENT: A STUDY IN THE BANKING SECTOR

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Abstract

This study examines the impact of Industry 4.0 based technological developments on the employment figures of Garanti Bank, Yapı ve Kredi Bank, Finansbank, and Denizbank between 2009 and 2020. For this purpose, the number of personnel, operating expenses, internet banking users, mobile banking users, customers, credit card users, ATMs, and POS devices were used as data. The study explores how banks respond to the demands of the evolving customer ecosystem through innovations brought by Fintech and Banking 4.0, which can be described as extensions of Industry 4.0 in the banking sector. The preferences of new-generation banking customers are analyzed in terms of traditional banking activities, such as the number of branches, the number of personnel, and related changes in personnel expenses. Additionally, reflections of technological advancements are examined through the number of internet banking and mobile banking users, as well as operating expenses a balance sheet item tracking investments in these areas. Furthermore, alternative distribution channels are analyzed, including the number of credit card users, ATMs, and POS devices.

Keywords: Industry 4.0, Number of personnel, Operating expenses, Number of internet banking users, Number of mobile banking users.

ENDÜSTRİ 4.0'IN İSTİHDAM ÜZERİNDEKİ ETKİSİ: BANKACILIK SEKTÖRÜNDE BİR ÇALIŞMA

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Özet

Endüstri 4.0'ın İstihdam Üzerine Etkisi: Bankacılık Sektörü Üzerine bir Araştırma isimli çalışmada, Garanti Bankası, Yapı ve Kredi Bankası, Finansbank ve Denizbank'ın, 2009-2020 yılları arasında Endüstri 4.0. temelli teknolojik gelişmelerin ilgili bankaların istihdam rakamlarını ne yönde etkilediği incelenmektir. Bu amaçla, bankaların personel sayıları, faaliyet giderleri, internet bankacılığı kullanıcı sayıları, mobil bankacılık kullanıcı sayıları, müşteri sayıları, kredi kartı kullanıcı sayıları, ATM sayıları ve POS sayıları veri olarak kullanılmıştır. Bankaların değişen müşteri ekosisteminin taleplerine, Endüstri 4.0.'ın bankacılık sektöründeki uzantısı olarak nitelendirebileceğimiz Fintech ve Bankacılık 4.0.'ın getirdiği yenilikler ile cevap vermesidir. Yeni nesil banka müşterilerinin isteklerine, geleneksel bankacılık faaliyet veileri olarak kabul edilen şube sayısı, personel sayısı ve bu iki kalemle bağlantılı olararak personel giderlerindeki değişmer, teknolojik gelişmelerin yansıması olan internet bankacılığı kullanıcı sayısı, mobil bankacılık kullanıcı sayısı ile bu iki kaleme yapılan yatırımların takip edildiği bilanço kalemi olan faaliyet giderleri ile alternatif dağıtım kanallarını temsil eden kredi kartı kullanıcı sayısı, ATM sayısı, POS sayısı incelenerek cevap aranmaktadır.

Anahtar Kelimeler: Endüstri 4.0, Personel sayısı, faaliyet giderleri, internet bankacılığı kullanıcı sayısı, mobil bankacılık kullanıcı sayısı.

1. INTRODUCTION

Banks are the foundation of national economies and have essential responsibilities in ensuring market stability. These include mediating financial services, providing liquidity, facilitating fund transfers and investment financing, managing maturity periods between short-term resources and medium-to-long-

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term investments, ensuring the effectiveness of monetary policy, and fostering national and international trade by offering various payment and credit options (Küçükbay, 2016). Due to these responsibilities, it is crucial for banks to maintain a healthy structure to ensure the economy can function effectively. The health of banks, in turn, is achievable by increasing their profitability. The four banks analyzed in this study recorded an average net profit increase of 96.21% between 2009 and 2020. It is expected that this increase would have a positive impact on employment figures. However, instead of investing in traditional banking instruments, banks have directed their profitability towards technological infrastructure and digitalization. By doing so, banks not only meet the demands of new-generation customers but also achieve the technological transformation required by the era, thereby maximizing their profitability.

In this context, the foundation of our research is twofold. First, it is based on the premise that the integration of technology driven by Industry 4.0 will reduce the demand for personnel and, in the near future, create a substitution effect for employees in the banking sector. Second, the relationship between technological applications in banking and operating expenses, as tracked in the balance sheets, has been examined. For this purpose, the activity reports of Garanti Bankası, Yapı ve Kredi Bankası, Finansbank and Denizbank from 2009 to 2020 were used as data sources. The innovations brought by Industry 4.0-based technology in banking are discussed as a literature review in the second section. In the third section, the effects of Industry 4.0 on employment data in the banking sector were analyzed using Panel Data Analysis, with 2009 serving as the base year for calculating change rates in the dataset. In the conclusion section, the findings from the Panel Data Analysis are interpreted.

The primary reason for conducting this study is the likelihood that sector employees may be unprepared for the disruptive technological advancements on the horizon. A significant portion of employees in the banking sector feel secure about their job stability due to the sector's strong capital accumulation, well-established institutional structure, and, most importantly, increasing profitability ratios. However, as this study reveals, the banking sector is making almost no investments in traditional banking instruments. The approximately 2% annual average increase in personnel numbers between 2009 and 2020 further supports this thesis. The aim of this study is to clearly demonstrate the correlation between the growth rate of employment figures and the increase in technology investments within the banking sector, which is under going transformation due to Industry 4.0-based technologies over a 12-year period. This, in turn, aims to encourage employees to reflect on the impact of these changes on their job security. For those currently employed in the banking sector or aiming to build a career in it, the second section offers insights into the tools introduced to the sector over the years by Industry 4.0. It is essential to remember that the banking sector is one of the leading industries in digitalization. While the profitability brought by Industry 4.0 innovations plays a crucial role, the primary reason for the sector's shift to digitalization is the demand for digital banking from the new customer ecosystem. Today, many bank customers not only use digital banking instruments such as internet banking and mobile banking but also employ various payment methods beyond cash, such as credit cards, overdraft accounts, wire transfers, EFT, PayPal, and more. The increase in the number of internet banking users, mobile banking users, credit card users, and POS devices between 2009 and 2020 in the banks analyzed in this study clearly demonstrates the growing customer demand for digital banking. Similarly, the rise in operating expenses, which reflect investments in technology, supports this argument.

Finally, for Model 1, the relationship between the dependent variable, number of personnel, and the independent variables operating expenses, number of internet banking users, number of mobile banking users, and number of credit card users were found to be insignificant in all tests conducted. However, the relationships with the number of customers, ATMs, and POS terminals were negative and significant. The significant relationship between the number of personnel and the number of customers indicates that the increase in customer numbers corresponds to traditional banking practices, which Musaev et al. (2020) refer to as Banking 1.0. A small portion of bank customers still prefer traditional banking services, while the majority of the new customer profile prefers digital banking. Furthermore, according to Musaev et al. (2020), the significant relationship between the number of personnel and the number of ATMs corresponds to Banking 2.0, while the relationship with the number of POS terminals corresponds to Banking 3.0.

For Model 2, there is a significant positive relationship between the dependent variable, operating expenses, and the independent variables: number of internet banking users, number of mobile banking users, and number of POS terminals. However, the relationships between operating expenses and the number of customers, ATMs, and credit card users are insignificant. According to Musaev et al. (2020), the significant relationships with internet banking users, mobile banking users, and POS terminals correspond to Banking 3.0 and Banking 4.0. The independent variables that showed a significant relationship with the dependent variable personnel number in Model 1 correspond to Banking 1.0 and Banking 2.0, while the variables with insignificant and negative relationships correspond to Banking 3.0 and Banking 4.0, reflecting the substitution effect of technology. Similarly, for Model 2, the independent variables significantly related to operating expenses correspond to Banking 3.0 and Banking 4.0, whereas the ATM variable, which showed an insignificant relationship, corresponds to Banking 2.0. There is a clear correlation between technology investments in the banking sector and technological developments.

2. LITERATURE REVIEW

Panel Data Analysis is an essential method for empirical studies conducted in the banking sector. Given that the datasets derived from banks' balance sheets and activity reports include both time and unit dimensions, Panel Data Analysis is the most suitable method for such studies. This approach enables the analysis of large datasets over extended time periods, allowing for the derivation of meaningful results.

Çelik and Uysal (2021) examined the market structure of the Turkish banking sector for the period between 2010 and 2019 using Panzar and Rosse (1987) model. The study utilized balance sheet data from 26 deposit banks operating in the Turkish banking sector. In the literature, studies estimating the H-statistic using the standard panel data method often note that the time dimension (T) is smaller than the number of banks (N). Additionally, the standard panel data method (particularly the fixed effects method) tends to estimate the Panzar and Rosse H-statistic with a bias, producing values close to zero. In cases where the time dimension is smaller than the number of banks, dynamic panel data (GMM) estimation provides more accurate results (Goddard et al., 2007). Therefore, the dynamic panel data method was preferred in the study to determine the market structure of the Turkish banking sector using the Panzar and Rosse H-statistic. The results revealed that the dominant structure in the Turkish banking sector during the analyzed period was a monopoly.

Bikker et al. (2012) used both static panel data and dynamic panel methods in their extensive study, which included data from 63 countries and 17,000 banks, to estimate market structures. Switala et al. (2013), in their study on the Polish banking sector for the period 2010–2012 using the dynamic panel data method, found that the market structure was characterized by monopolistic competition. Mustafa and Toçi (2017), in their analysis of the banking sector in 17 Central and Eastern European countries for the period 1999–2009, identified the market structure as a monopoly. Ildırar & Başaran (2021), in their study on the Turkish banking sector using the dynamic panel data method for two sub-periods, determined that the market structure was monopolistic competition throughout the period 2003–2018. However, they observed a decrease in competitive structure after the 2008 Global Financial Crisis. Meta et al. (2021), in their research aimed at determining how regulations affected the level of competition in the Turkish banking sector, used the extended mean group method. They found that while regulations positively influenced competition, the H-statistic value was close to "0," indicating a monopolistic structure.

Değer and Doğanay (2017) used Panel Cointegration Analysis between 1996 and 2014 to examine the relationship between FDI (Foreign Direct Investments) and exports in Emerging Market Economies. The study initially provides results of homogeneity, cross-sectional dependence, and unit root tests for 21 emerging market economies, reflecting FDI, total merchandise exports, and manufacturing industry exports during the 1996–2014 period. In the following sections of the study, panel data cointegration analyses were used. The results of the panel cointegration tests revealed that there were long-term and statistically significant cointegrated relationships between FDIs and both total merchandise exports and manufacturing industry exports in these countries.

Küçükbay (2017) used 28 deposit banks operating in Turkey as a sample in his research. The study aimed to analyze the factors affecting the profitability of deposit banks and examined whether there are any differences in the profitability determinants between Turkish and EU banks. In the research, data from the period between 2009 and 2013 were used for comparison with the study by Menicucci and Paolucci (2016). As a result, the study showed that both bank size and capital ratios have a statistically significant impact on the return on assets (ROA) of both Turkish and EU banks.

Tiryaki (2012) examined the relationship between financial stability and banking system regulations using a two-stage method. In the first stage, a financial stability index was created that included the banks' intermediation role, differing from the Central Bank of the Republic of Turkey’s (CBRT) financial stability index. Then, the study analyzed the role of four key banking regulatory tools capital adequacy, provisions for non-performing loans, liquidity adequacy and reserve requirements within the context of financial stability in the Turkish banking system. These tools were analyzed in terms of their role in maintaining financial system stability over both short and long periods. According to the study, the connection between the Financial Stability Index and the key banking regulatory tools is explained through an econometric model based on the cointegration method. The most important finding of the study is the positive relationship between banking regulations and financial stability.

Çam and Özer (2018) analyzed data from a total of 27 deposit banks operating in the sector during the period from 2003 to 2012 using a panel data set. In their study, they considered a model that takes the scale variable into account, where the H value was calculated to be 0.13, and a model that did not consider the scale variable, where the H value was calculated to be 0.79. As a result, it was concluded that the Turkish banking sector operates under monopolistic competition conditions, and that scale size is an important variable affecting market structure.

Meta et. al. (2021) used Panel Data AMG analysis to examine the legal regulations and market structure in the Turkish banking system. To achieve the objective of the study, they first determined the market structure of the sector by using the Panzar-Rosse H Statistic. The equation was estimated using a panel data set of 27 banks. As a result, the equation created to measure the impact of regulations on market structure was estimated using the AMG estimator. The study found that, during the 2000-2018 period, regulations had a competition-enhancing effect in the Turkish banking sector.

Yıldırım (2013) examined the efficiency of foreign-owned deposit banks in the Turkish banking sector, comparing them with domestic-owned deposit banks. Panel data analysis was used in this study. The scope of the study includes the deposit banks group, which represents the entire sector, as well as the foreign banks group that has 50% or more foreign ownership under the deposit banks category. As a result, the restructuring program in the Turkish banking sector was successful, and it paved the way for foreign investors to enter the country.

Karamustafa and Yıldırım (2007) conducted a study in Kayseri province using a survey method to investigate the factors that influence customers' bank preferences. The study found that the most important factors were the bank's reliability, the absence of queues, ATM availability, and an extensive service network.

Elmas and Polat (2016) used panel data analysis to investigate the impact of R&D investments on firm performance. The study utilized data from the period 2007-2014, with data sourced from the Istanbul Stock Exchange and the Public Disclosure Platform (KAP). The results showed that the impact of R&D investments on the manufacturing sector was generally negative.

Berke (2009), used panel data analysis to examine the relationship between the debt stock of the European Monetary Union and inflation. The results of the analysis indicated that for each group, fiscal policy played no role in determining the price level (the Fiscal Theory of the Price Level - FTPL was not valid). Instead, only monetary variables were found to be significant, suggesting that the Ricardian regime was valid.

Musaev et al. (2020) used regression analysis to examine the economic outcomes of Sberbank Russia's customer-centric digital transformation. The dataset used for this study consisted of the bank's annual reports from 2014 to 2017. The results showed that the digitalization efforts had a positive impact on the bank's profitability. Additionally, the customer base had increased, the range of non-financial services offered by the bank had expanded, and there was a rise in financial savings due to the reduction of offices and staff performing banking transactions in the traditional business model.

Rojko et. al. (2020) used cross-correlation analysis to investigate the transformative effects of Industry 4.0 in the manufacturing sector in USA. The study analyzed data from 2018-2019, using sources such as the U.S. Bureau of Labor Statistics, the Federal Reserve, and the World Bank. The findings indicated that during the transition to Industry 4.0 in USA, there was a slight increase in manufacturing output, workforce productivity, number of employees, and labor efficiency. However, expectations for the next decade suggest brighter prospects, with the development and implementation of AI and robotics projected to drive higher labor productivity and, consequently, increase overall prosperity.

3. THEORETICAL BACKGROUND

Industry 4.0 is a transformative process that fundamentally changes production and service processes through the integration of technologies such as digitalization, automation, artificial intelligence, and big data. The banking sector is directly affected by this transformation and is experiencing significant changes in its workforce structure. This study examines employment theories based on Industry 4.0 within the context of the banking sector and analyzes the impact of technological advancements on the workforce.

3.1.Technological Substitution Theory

With Industry 4.0, many routine and repetitive tasks in banking are being performed by automated systems and artificial intelligence. For example, technologies such as ATMs, mobile banking, and internet banking have taken over a significant portion of traditional branch operations (Musaev et al., 2020). This situation leads to a decrease in personnel numbers in positions such as branch staff and tellers, while simultaneously creating new job areas to support digital operations.

3.2. Changing Skill Requirements and Job Restructuring

Technological advancements have altered the job descriptions of banking employees. Bank staff are no longer only responsible for customer service but must also effectively use digital tools and acquire competencies in new areas such as data analysis and cybersecurity (Rossini et al., 2019). In this context, continuous training and skill development programs are critically important in the sector.

3.3. Multiple Roles and Flexible Work Models

Industry 4.0 has increased the need for a flexible and multitasking workforce in banking. Remote work, hybrid models, and managing business processes through digital platforms require employees to be more adaptable and flexible. This change introduces new dynamics in terms of work-life balance and motivation (Cividino et al., 2019).

3.4. Creative Employment and Innovation

The banking sector utilizes the technological infrastructure brought by Industry 4.0 to develop new financial products and services, increasing innovation-focused positions. In this process, employees' innovation skills come to the forefront, creating new employment opportunities in areas such as R&D, data science, and digital marketing (Muscio and Ciffolilli, 2020).

3.5. The Quantitative and Qualitative Impact of Digitalization on Employment

While there is a partial decrease in the number of personnel in banking, the demand for workforce in new specialized fields to manage digital technologies is increasing. This indicates that employment is contracting quantitatively but diversifying and deepening qualitatively (Mrugalska & Wyrwicka, 2017). In particular, areas such as data analysis, AI-supported customer management, and cybersecurity have become critical.

3.2. INDUSTRY 4.0

3.2.1. Historical Process of Industry 4.0

The concept of Industry 4.0 emerged as a high-tech thematic project initiated by the German government. The project, developed with the approach of digitalizing production, was inspired by significant transformations in past industrial revolutions. The concept was first introduced in 2011 at Hannover Messe (Banger, 2016).

The First Industrial Revolution began in the late 1800s with the introduction of steam-powered machines. The significant advancements in industry allowed Europe to gain superiority over other regions in many fields, especially in the economy, and this period was therefore defined as the "Industrial Revolution" (EBSO, 2015). The Second Industrial Revolution first emerged in the United States, and is defined by the introduction of electricity into industrial production, which led to the start of mass production. With the advent of mass production, the prices of industrial goods decreased, making them more accessible to people. The Third Industrial Revolution, which began in the 1970s, is marked by the introduction of electronics and the beginning of the automation age. The automation of production processes with digital technology and IT in Industry 3.0 brought a new dimension to production technologies, leading to the development of the first microcomputers. The Fourth Industrial Revolution focuses on the digitalization of all assets and the large integration of participants.

3.2.2. Key Features of The Fourth Industrial Revolution

Industry 4.0 is seen as a crucial strategy for survival in perfectly competitive markets. Companies are focusing on Industry 4.0 to address issues such as increasing product customization, resource efficiency, and reducing time to market. This also includes competitive product design and implementation, flexible logistics, and production systems (Rennung et al., 2016). According to another definition, Industry 4.0 refers to the formation of autonomously organized value chains that will provide optimum quality in planning, engineering, production, operations, and logistics, offer more flexibility and resilience, and at the same time can be designed according to various criteria such as cost, availability, and resource consumption (Acatech, 2013).

The fundamentals of Industry 4.0 can be summarized as follows:

- **Internet of Things (IoT):** The concept of IoT was first introduced by British entrepreneur Kevin Ashton. The Internet of Things is expected to create significant economic opportunities and has the potential to bring about a technological revolution (Hofmann & Rüsch, 2017). IoT is a key factor in the transition from the Third Industrial Revolution to the Fourth Industrial Revolution. Also known as the Industrial Internet, its foundation lies in smart factories, products, and services. The Internet of Things can be defined as the classification, circulation, and organization of data coming from different sources in a production system (Alçın, 2016).
- **Big Data:** Big Data refers to datasets that exceed the capabilities of typical database software for recording, analyzing, and managing data. However, this definition is subjective, and there is a fluid definition about the size of a dataset required to be considered Big Data. As technology progresses, it is expected that the size of Big Data sets will increase as well (McKinsey, 2011). Big Data data is collected from sources such as internet servers' logs, internet statistics, social media, blogs, microblogs, climate sensors, mobile network operators, etc.

- **Cyber-Physical Systems (CPS):** CPS are structures that involve the interaction and coordination between the real world and the cyber world (Sinan, 2016). The most important function of CPS is to meet the dynamic requirements of production, thereby increasing its efficiency. CPS combines the real and virtual worlds, activating technologies that create a new universe connected to a physical network, facilitating the interaction of smart objects. CPS and advanced sensor networks represent the next evolution of existing embedded systems. Along with online data and services, sensors are the fundamental components that make up cyber-physical systems (Dai et al., 2012; Alçın, 2016).
- **Cloud-Based Manufacturing (CBM):** CBM refers to applications that allow data to be stored in the cloud and enable interaction with devices in the internet environment, commonly known as Cloud Computing (EBSO, 2015). CBM is another paradigm that will significantly contribute to the success of the Fourth Industrial Revolution. CBM can be defined as a model of reconfigurable cyber-physical production lines that increases efficiency, allows optimal resource allocation for products, and responds to customers' continuously changing and evolving demands.
- **Smart Factories:** Developed countries invest in national initiatives to promote advanced manufacturing, innovation, and design in the global world. A significant portion of these investments is spent on building a future where smart factories and manufacturing, which form the foundation of the Fourth Industrial Revolution, are the norm. The Fourth Industrial Revolution is defined as "smart manufacturing," where all objects can be integrated through the Internet of Things (IoT), driven by developments in areas such as AI, 3D printers, and Cloud Technology. In Industry 4.0, one of the places where objects communicate is "smart factories," also known as "dark factories," where no humans are involved due to the deployment of smart technologies. In the first dark factory, established in China to produce mobile phone modules, the use of robots reduced the workforce by 90%, while the product defect rate decreased from 25% to 5% (Aksoy, 2017).
- **Virtual Reality (VR):** VR is a three-dimensional model that offers participants a realistic experience, providing the opportunity for interactive communication within a dynamic environment created by computers (Bayraktar & Kaleli, 2007). Virtual reality can be utilized in many aspects of industrial production, including planning, design, manufacturing, service, maintenance, testing, quality control, etc. In these aspects, VR plays a fundamental role in Industry 4.0. For example, to predict how efficiently a factory will operate, the factory can be virtually built and run in a simulated environment before its physical construction. The resulting data can then be analyzed. This analysis can be carried out not only at the factory level but also on individual production processes or machines, allowing for detailed examination.
- **3D Printers:** 3D printing is the process of creating a physical object from a digital design by layering materials made of very fine, melted layers (Montess, 2016). 3D printers can be used in various sectors, ranging from genetic science technologies to industries, by utilizing a wide range of material combinations.
- **Artificial Intelligence (AI):** Colom et al. (2010) define AI as a general mental ability for reasoning, problem-solving, and learning. Snyderman and Rothman (1987) also describe AI as a general mental ability for reasoning, problem-solving, and learning. In the early years of the 21st century, due to the availability of large data sets, powerful computer hardware, and new methodologies, investments in artificial intelligence significantly increased. In this century, AI has evolved from an academic field to an important factor in technologies used in social and economic life, including banking, medical diagnostics, and autonomous vehicles (Frank et al. 2019).

Fintech companies are increasingly using artificial intelligence applications for various purposes, including risk, risk measurement, fraud, and consumer protection. Other important use cases include credit scoring, chatbots, capital optimization, market impact analysis, and finally, 'reg tech' applications (Paul, 2019).

Digital tools, such as artificial intelligence, can help solve the problem of inormation asymmetry (Kaya & Pronobis 2016). Through AI, digital financial inclusion can aid in reducing information asymmetry between financial institutions and individuals, as large amounts of information about individuals can be generated through various online shopping platforms and social networks (Wang and He, 2020; Yang and Zhang, 2020). Digital tools, particularly those based on big data analysis and cloud computing, can enable access to credit for vulnerable sectors without collateral (Wang and He, 2020). Many digital technologies utilizing AI use alternative credit scoring mechanisms to create unsecured credit products (Matsebula and Yu, 2017). One of the most significant examples of banks offering unsecured credit is the Grameen Bank, which won the Nobel Peace Prize in 2006 alongside Prof. Muhammad Yunus. The bank has provided $24 billion in unsecured loans to borrowers (Karlan and Morduch, 2010; Wang and He, 2020).

3.2.3. Banking 4.0.

Today, the rate of digital transformation in the banking sector and the entire economic ecosystem is extremely high. These changes are having an unprecedented impact on the dynamism of individuals and socio-political society. Increased data utilization, the use of AI-based machines, IoT, and digital technologies play a significant role in this process.

Table 1. Evolution of the Banking Sector

Conceptual Period	Drivers	Banking Services	Characteristics of Banking Activities
Banking 1.0.			Activities are based on classical management principles
			Standard services are provided for individuals and firms, and financial intermediation is offered.
Banking 2.0.	ATM's	The active distribution of ATMs in cities. Banking has acquired a new appearance.	Although banking has acquired a new appearance, classical banking principles are still applied.
1990's	İnternet	Access to banking services has become possible through remote communication channels.	Service delivery channels are expanding. Digitalization is beginning.
Banking 3.0	Smart Phone, Big Data, LoT, Cluod Tek.	The need to visit bank branches has reached a minimum level.	Banks are actively building their own ecosystems and partners. Services and business processes are becoming digitalized, and efficiency is increasing.
Banking 4.0.	VR, AI	The use of artificial intelligence and virtual reality technologies in banking services.	The bank has become a tool that is actively integrated into the end user's life, enabling you to meet their needs 'here and now.' Customers can make optimal financial decisions using AI.

In Table 1, It has been argued that digital applications offer an enhanced banking experience; therefore, the banking sector is conducting innovative technological experiments to support mobility and increase the speed and efficiency of customer transactions (Harjanti et al., 2019). Previous studies have emphasized that the biggest dilemma for the current banking system is the profitability tied to branch-oriented revenue growth alongside the high costs of traditional banking (Capgemini, 2012).

The banking system is a cornerstone of economic growth and macroeconomic stability, especially in the context of globalization. However, the evolution of the banking sector in each country is influenced by the constantly changing dynamics of the international banking system (Spulbar and Birau, 2019). Today, even technology companies can offer banking services through FinTech based applications. From the recent past to the present, the banking sector in almost every country around the world has been leveraging the advanced technologies brought by the Industry 4.0 revolution. Some of these advantages include increased efficiency, innovative products, fast transactions, seamless transfer of funds, real-time information systems, and efficient risk management (Saravanan et. al., 2016). Financial deregulations are supported by the revolution in information and communication technology, enabling banks to innovate in their products and services at competitive prices.

There are three options for implementing modern technologies in banking:

- Establishing a new bank (neobank, online bank, direct bank).
- Building a digital bank from scratch as a continuation of a traditional banking system.
- Collaborating with FinTech services to enhance the customer interface, digitize processes, and expand the offering of data-driven analytical products.

Maturity models are comprehensive guides used to define and evaluate the current state of the banking sector in its journey toward Industry 4.0 (Bandara et al., 2019). Other researchers have developed a maturity model considering the capability dimension of the existing Software Process Improvement and Capability Determination (SPICE) model (Gökalp et al., 2017). On the other hand, the Technology Acceptance Model is widely regarded as the most influential theory in IT (Benbasat & Barki, 2007).

Heffernan (2005) suggests that banks represent financial firms, offering credit and deposit products to the market and serving the changing liquidity needs of consumers such as borrowers and depositors. However, banks aim to provide higher-quality services to customers by increasing their technological capabilities and levels of technological advancement, which in turn demands greater transparency. Establishing an efficient and robust banking system is a crucial prerequisite for sustainable economic growth (Spulbar and Birau, 2019).

3.2.4. Fintech

The term "FinTech," a combination of the words finance and technology, first emerged in Anglo-Saxon media during the 1980s and 1990s. However, following the 2007 financial crisis, digital, mobile, artificial intelligence, and similar technologies began to be utilized to redesign banking services to be faster, cheaper, and more efficient.

Technological advancements make it possible to rebuild the financial sector by creating new products and opportunities, even threatening the core market players within the industry. FinTechs enable entry into customer-focused areas neglected by major market actors. Applications popularized by mobile phones, alongside changes in software and engineering, have intensified internet usage, significantly impacting not only the financial sector but also many other industries.

Mobile and digital payment systems continue to be the main strength of FinTechs. Additionally, banking APIs, Artificial Intelligence, Personal Finance, Retail Investments, Corporate Investments, P2P lending, Crowdfunding, Asset Management, Money Transfers, Big Data and Analytics, Financial Platforms, InsurTech, RegTech, Blockchain and Cryptocurrency Technologies, Robot Assistants, and Next-Generation Banking are among the many technologies included in the service offerings of FinTech.

FinTech is considered one of the most significant innovations in the financial industry, and it is rapidly developing, partially driven by the sharing economy, favorable regulations, and information technology (Lee & Shin, 2018). FinTech systems provide new and advanced business models, such as crowdfunding, P2P, and B2B, using innovative technologies. As a result, the traditional banking business model faces significant challenges (Dasho et al., 2017). The growth of FinTech is defined as an ongoing process that integrates the rapidly evolving technology into the financial ecosystem (Arner et al., 2015). FinTech aims to reshape the financial industry by reducing costs, enhancing the quality of financial services, and creating a broader and more stable financial ecosystem. In this context, there are five key determinants for FinTechs:

- FinTech startups (e.g., payments, wealth management, lending, crowdfunding, capital markets, and FinTech insurance companies),
- Technology developers (e.g., big data analytics, cloud computing, cryptocurrency, and social media developers),
- Government (e.g., financial regulators and legislative bodies),
- Financial customers (e.g., individuals and organizations),
- Traditional financial institutions (e.g., traditional banks, insurance companies, stockbroker firms, and venture capitalists).

3.2.5. Digital Banking

Technological advancements in the global economy have introduced new concepts within the financial sphere. The new economic model that emerged with the widespread use of the internet is defined by IT focused new economy concept, while also presenting the phenomenon of "capitalism without capital." Today, intangible investments have surpassed tangible investments like machinery, equipment, and vehicles. Therefore, it is more accurate to describe today's production model as "capitalism without capital." In this context, the digital transformation referred to as the Fourth Industrial Revolution is not only about the rise of machines, but also about empowering people (Keywell, 2017). According to Keywell (2017) billions of people and countless machines are interconnected. With this new technology, unprecedented processing power, speed, and large storage capacities allow data to be collected and utilized in ways that were never possible before.

At the current stage, intangible investments have surpassed tangible investments such as machinery, equipment, and vehicles. Therefore, there is a perspective that interprets today's production model as "capitalism without capital." In this context, the digital transformation, referred to as Industry 4.0, is described as not about "the rise of machines, but about empowering people" (Keywell, 2017). According to Keywell, billions of people and countless machines are interconnected. With this new technology, unprecedented processing power, speed, and large storage capacities allow data to be collected and utilized in ways that were never possible before.

Digital transformation is a holistic change in the business world that occurs in response to new opportunities created by rapidly developing information and communication technologies, as well as changing societal needs. This transformation aims to provide more efficient and effective services, ensuring user satisfaction by integrating human factors, business processes, and technology. The level of development in societies is clearly reflected in this transformation. For example, the internet has become an essential part of daily life from the 2000s onwards. In 2005, the global number of internet users was one billion, and by 2020, this number had reached 4.5 billion. There is a strong correlation between the speed of internet access in countries and their economic, technological, and cultural development. For example, in North America, internet access is 88.1%, whereas in Sub-Saharan Africa, it is just 20%. Today, the internet is widely used in areas such as sales, marketing, service, and product design.

According to Negroponte's (1995) knitting model, learning a knitting pattern involves a process where a tailor learns by observing, applying, and physically engaging with the work. In this process, for another expert to learn a manually performed task, it would require the tailor to teach them or for the product to be examined. However, if a database is created to collect digital knitting models, a wide variety of patterns can be selected instantly, and new designs can be created in a very short time using different combinations. These newly designed models can be rapidly sent to any location in the world and reproduced as many times as desired. In this context, digitalization in the workflow brings forward important functions, such as:

- Perfect copies,
- Low cost,
- Advanced processes such as searching, analyzing, correcting, and developing.

The perspectives of managers on digital transformation are crucial in determining the future of industries. In this context, a joint study was conducted by TÜSİAD, Samsung, GfK, and Deloitte (2016). This study, titled "CEO Perspective on Digital Change," involved interviews with senior executives from various sectors and examined the country's digital transformation process. The banking sector responded the earliest to digital transformation. According to the results of the study, the reasons for digital change in the banking sector were as follows:

- Competitive advantage (36%),
- Increased efficiency (20%),
- Speed in meeting customer needs (18%),
- High profitability (16%).

At this stage of the study, when examining the external factors affecting the banking sector, it was found that the impact of digital technologies is significant. The top three external factors for banks are:

- Macroeconomic effects (26%),
- Regulations (19%),
- Digital technologies (19%).

3.2.6. Open Banking (OB)

OB is a newly emerging and rapidly developing field within financial systems (Open banking homepage, 2018). This application focuses on data sharing through API (Application Programming Interface) interfaces. Applications can be developed that collect banking data from different institutions via APIs and present them on a single platform. APIs are sets of connection applications that enable communication between each other and serve as an interface between different applications. In addition to their other advantages, APIs also help save costs; that is, they offer a relatively inexpensive and simple way to transfer data from one application to another. These applications can be developed not only by internal programmers but also by external developers (Kandırmaz et al. 2018).

OB enables Industry 4.0 organizations to explain data, algorithms, and processes through application programming interfaces, allowing them to create new revenue models. The ANOB (API-based Open Banking) model also offers new opportunities for product creation and distribution. In Industry 4.0, the banking sector has undergone significant changes, involving numerous partners in the product development process. In this new approach, the importance of APIs has been emphasized.

Fidor Bank has significant experience in developing revenue transfer around API-based businesses. While banks typically generate revenue through community banking models, net interest income, fees, and commissions, APIs generate approximately one-third of their revenue from white-label solutions (products or services produced by one company but resold by another).

OB and Banking 4.0 have been incorporated into the evolution of banking. The distinction of APIs lies in their ability to collect operational data from various sources, including customers' purchasing habits, financial needs, and risk appetite. This enables banks to offer products and services to customers through different tools and channels. To achieve this, banks collaborate with FinTech companies to design various products, thereby significantly increasing product distribution and maximizing customer satisfaction.

3.2.7. Robotic Process Automation (RPA)

Robotic technology is revolutionizing the way many banking and financial companies operate through a tool known as RPA. According to Romao et al. (2019), RPA represents the use of software with AI and machine learning capabilities to manage high-volume, repetitive tasks that were previously only possible for humans to perform. RPA is a virtual business model based on conservative software, focusing on tasks that humans are good at but that are less tedious. For instance, PayPal and credit institutions use robots to serve their clients. The PayPal robot uses its program to transfer money from one person to another. PayPal also interacts with robots from companies like Uber. MasterCard has created a robot for its customer service department and for the Masterpass application. Bank of America has created a robot for cardholders on Facebook. According to

Mladenovic (2018), RPA is a fast and simple way for banks to automate a wide range of processes. In this context:

- Ensuring efficient interaction between different systems, thus eliminating the need for employees to manually generate data sources.
- Improving middle and back-office processes (faster execution, fewer errors).
- Accelerating the processing of big data.
- Freeing up employees to focus more on customers and provide a better customer experience.
- Simplifying regulatory compliance with greater transparency.
- Paving the way for a new wave of transformation toward 100% digital banking.

4. AIMS OF THE EMPIRICAL STUDY

In this study, the relationship between the number of bank personnel (dependent variable) and the technology investments in their balance sheets (tracked through operational expenditure) and the use of new generation technologies in banking (such as the number of internet banking users, number of mobile banking users, number of credit card users, number of ATMs, number of POS devices, and the number of bank customers) was analyzed in Model 1 for the period between 2009 and 2020. In Model 2, the dependent variable was the operational expenditure tracking technology investments, while the relationship with internet banking users, mobile banking users, credit card users, ATM numbers, POS numbers, and the number of bank customers was also examined. For this purpose, the activity reports of Garanti Bank, Yapı ve Kredi Bankası, Finansbank, and Denizbank from their annual reports, published on the banks' own websites, were used from the years 2009 to 2020.

The aim of this study is to use the data disclosed in the banks' activity reports to examine the employment status of the sector and how the thesis of "machines replacing human labor" in the context of Industry 4.0 technological developments has evolved in the banking sector over the relevant years. Today, as Nikola Tesla once said about workers, "Machines made flesh," we are witnessing the transition of the sector into a fully mechanized process with the Industry 4.0 revolution.

The data collection tool used in this study includes:

- Garanti Bankası A.Ş. Activity Reports for the years 2009-2020,
- Yapı ve Kredi Bankası A.Ş. Activity Reports for the years 2009-2020,
- Finansbank A.Ş. Activity Reports for the years 2009-2020,
- Denizbank A.Ş. Activity Reports for the years 2009-2020,
- Central Bank of the Republic of Turkey (T.C. Merkez Bankası),
- Banking Regulation and Supervision Agency (BDDK)

4.1. Panel Data Analysis

Panel data analysis, which combines cross-sectional dependence and time series, was first discussed in the works of Hildreth (1950), Kuh (1959), Grunfeld and Griliches (1960), Zellner (1962), Balestra and Nerlove (1966) and Swamy (1970).

Panel data analysis, which uses cross-sectional data with both time and unit dimensions, refers to the estimation of economic relationships through panel data models. In this analysis, it is generally encountered that the number of cross-sectional units (N) exceeds the number of periods (T) (N > T).

The panel data model is generally;

$$Y_{it} = \alpha_{it} + \beta_{it} X_{it} + u_{it} \quad i=1,\ldots\ldots,N;\ t=1,\ldots\ldots,T$$

Here, Y is the dependent variable, Xk are the independent variables, α is the constant parameter, β are the slope parameters, and u is the error term. The subscript i refers to the units (such as bank, individual, firm, city), and the subscript t refers to time (such as day, month, year). The fact that the variables, parameters, and the error term have both i and t subscripts indicates that they are part of a panel data set. In this model, the constant and slope parameters take values according to both the units and time.

4.2. Empirical Research and Findings

Model 1: The relationship between the dependent variable of the number of employees (representing employment data) and the independent variables, such as technological developments expressed by operational expenses, internet banking users, mobile banking users,

number of customers, credit card users, ATM count, and POS count, from 2009 to 2020 for the relevant banks, is examined using Panel Data Analysis.

PSit ==βi+β1FGit+ β2İBit+ β3MBit+ β4MSit+ β5KKit + β6ATMit + β7POSit +u

Here, the index ***i*** represents the number of banks (1, 2, 3, 4, etc.), while the index ***t*** represents the time period (2009, 2010, …, 2020). ***u*** denotes the error term.

Model 2: The relationship between the dependent variable, which is the operating expenses representing technological development data, and the independent variables such as the number of internet banking users, the number of mobile banking users, the number of customers, the number of credit card users, the number of ATMs, and the number of POS devices was examined using Panel Data Analysis.

FGit ==βi+β1İBit+ β2MBit+ β3MSit+ β4KKit+ β5ATMit + β6POSit +u

Here, the index ***i*** represents the number of banks (1, 2, 3, 4, etc.), the index ***t*** represents the time period (2009, 2010, ..., 2020), and ***u*** represents the error term.

4.3. Homogeneity Test

The homogeneity test, within the scope of panel data analysis, aims to determine whether a change occurring in one of the banks affects the other banks at the same level. To test the homogeneity of the slope coefficients, the Pesaran and Yamagata (2008) test has been used.

In the test result, if the 0.00 < P-value < 0.05:

In the Table 2, the test results for Model 1 and Model 2 show that the slope coefficients are homogeneous. This is because the P-values are greater than 0.05.

Table 2. Slope Heterogeneity Test

	Delta	**P-dvalue**
PS Dependent variable	1.21	0.226
Adj.	2.420	0.016
FG Dependent variable	0.49	0.624
Adj.	0.848	0.396

In Table 2, Inter-unit correlation is known as cross-sectional dependence, which indicates that there is correlation between the error terms calculated for each unit of the panel data model. If we test the P-value, 0.000 < P-value < 0.005, the hypotheses are:

H0: No cross-sectional dependence,

H1: Cross-sectional dependence.

The acceptance of **H1** shows the presence of cross-sectional dependence.

Table 3. Cross-Sectional Dependence Test

Variable	CD-test	p-value	Average T	Average	Average abs(ρ)
PS	6.546	0.000	12.00	0.77	0.77
FG	8.281	0.000	12.00	0.98	0.98
İB	8.006	0.000	12.00	0.94	0.94
MB	8.112	0.000	12.00	0.96	0.96
MS	8.391	0.000	12.00	0.99	0.99
KK	6.64	0.000	12.00	0.78	0.78
ATM	6.896	0.000	12.00	0.81	0.81
POS	6.532	0.000	12.00	0.77	0.77

Notes: In Table 3, Under the null hypothesis of cross-sectional independence, CD ~ N(0,1). P-values close to zero indicate that the data is correlated across the panel groups.

4.4. Model Determination

In general, if it is assumed that all observations are homogeneous, meaning there are no unit and/or time effects, the classical model is considered appropriate. On the other hand, if it is assumed that there are unit and/or time effects, it is more logical to use a fixed or random effects model.

An F-test will be used to test the validity of the classical model.

F Test To Test The Presence of Unit and Time Effects

Table 4. Unit and Time Effects Regression PS, FG

PS	F test all u_i	0: F(11,29)= 1.25	(Explained Variance Fraction)	Prob > F	0.3011
FG	F test all u_i	0: F(11, 30) = 1.90	(Explained Variance Fraction)	Prob > F	0.0804

In Table 4, the formulated hypothesis, F-statistic, and p-value are provided. The test is conducted by comparing the test statistic with the F-distribution table, with degrees of freedom of (N1=11, (N(T-1)-K=30). According to the results, the null hypothesis (H0) stating that the unit effect is equal to zero is accepted, indicating that unit effects do not exist. Additionally, the null hypothesis (H0) stating that the time effects are equal to zero is also accepted, suggesting that time effects are significant. Therefore, the classical model is suitable. That is:

(Prob>F)= 0.0804 > 0.05

H0: Hypothesis is accepted. Random effects exist.

H1: Hypothesis is rejected. Fixed effects do not exist.

4.5. Hausman Test

The Hausman (1978) specification test (1978), developed to test for specification errors, is commonly used in various fields. In the context of panel data models, the purpose of the Hausman test is to make a choice between estimators.

The Hausman test is applied to test the null hypothesis (H0), which states "the difference between parameters is not systematic, in other words, the random effects model is appropriate," against the fixed effects model. In Stata, before applying the Hausman test, the fixed and random effects models need to be estimated separately.

- b = consistent under both H0 and Ha; obtained from xtreg
- B = inconsistent under Ha, efficient under H0; obtained from xtreg

For both Model 1 and Model 2, since Prob>chi2>0.05, random effects are present. The following table (Table 5) presents the Hausman test results for the dependent variables PS and FG.

Table 5. Hausman Test Results. PS, FG

Hausman Test Results for PS	chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 7.01	Prob>chi2 = 0.3201
Hausman Test Results for FG	chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)= 16.77	Prob>chi2 = 0.102

4.6. Heteroskedasticity and Autocorrelation In The Random Effects Model

In panel data models, heteroskedasticity refers to the situation where the error term does not have equal variance within units and across units. Additionally, autocorrelation refers to the temporal and spatial relationships in the error term. In the random effects model, since the inter-unit relationship is caused by random effects, inter-unit correlation is also expected. For this reason, tests for heteroskedasticity, autocorrelation, and inter-unit correlation are conducted in the random effects model.

In the random effects model, heteroskedasticity is tested using the Breusch-Pagan Lagrange Multiplier (LM) test, as well as the tests developed by Levene (1960), Brown and Forsythe (1974).

Table 6. Levene, Brown, and Forsythe Test PS, FG

HETEROSKEDASTICITY IN THE RANDOM EFFECTS FOR PS	W0 = 1.2271375	df(3, 44)	Pr > F = 0.3111619
	W50 = 1.1108030	df(3, 44)	Pr > F = 0.3549196
	W10 = 1.1435089	df(3, 44)	Pr > F = 0.34207099
HETEROSKEDASTICITY IN THE RANDOM EFFECTS FOR FG	W0 = 4.5811614	df(3, 44)	Pr > F = 0.00707561
	W50 = 4.2758219	df(3, 44)	Pr > F = 0.00983656
	W10 = 4.7350468	df(3, 44)	Pr > F = 0.00600203

In Table 6 above shows the means and standard deviations of the residuals for the units. The test statistics of Levene (1960), Brown and Forsythe (1974) are compared with the critical values from the Snedecor F distribution with (3,44) degrees of freedom. As a result, the null hypothesis stating that "the variances of the units are equal" is rejected, indicating the presence of heteroskedasticity.

4.7. Autocorrelation In The Random Effect Model

One of the assumptions in the random effects model is the assumption of autocorrelation in the error term. This is particularly a restrictive assumption in economic studies, as correlation over time in the error components (Vit = Uit + μi) is frequently observed in the random effects model. If autocorrelation is ignored during estimation, the parameters may be consistent but not efficient, leading to biased standard errors. In the random effects model, the presence of autocorrelation is tested using Durbin-Watson (DW) test by Bhargava et. al. (1982), as well as Baltagi-Wu's local best invariant tests (Tatoğlu 2016).

Table 7. Regression of RE, GLS with AR(1) Disorders. PS, FG

PS	Modifiye Bhargava ve Durbin-Watson	1.1657476
	Baltagi-Wu LB	1.4535467
FG	Modifiye Bhargava ve Durbin-Watson	0.96241728
	Baltagi-Wu LB	1.4077912

In Table 7 above, the DW test proposed by Bhargava et. al. (1982), as well as the LBI test statistic proposed by Baltagi-Wu, are shown. In the random effects model, the critical values for both tests are smaller than 2, which leads to the conclusion that there is first-order autocorrelation in the random effects model.

4.8. Resistant Estimators and Methods In The Presence Of Heteroskedasticity, Autocorrelation, and Inter-Unit Correlation

In this section, the aim is to adjust the standard errors (resistant standard errors) without altering the predictions of the Random Effects model used in our study. To achieve this, we will use the Huber, Eicker, and White Estimator Model.

Table 8. Random Effects Regression. PS, FG

PS	Robuts Standard Error	z	P>|z|		Robuts Standard Error	z	P>|z|
FG	0.0001446	-0.63	0.531	**FG**			
İB	0.0002706	-0.08	0.934	**İB**	0.1524485	2.12	0.034
MB	0.0003501	-1.02	0.308	**MB**	0.071182	35.9	0
MS	0.0000306	11.71	0	**MS**	0.2177178	1.04	0.299
KK	0.0000631	-1.89	0.059	**KK**	0.1952045	0.83	0.406
ATM	0.1304681	5.06	0	**ATM**	587.2245	-1.26	0.206
POS	0.0016401	7.26	0	**POS**	1.043189	7.04	0
CONS	447.5121	16.66	0	**CONS**	1487360	0.87	0.382
Observer number:48	Wald chi2(6)	Wald chi2(6)	-	Observer number:48	Wald chi2(6)	-	
Group number:4	Prob > F	Wald chi2(6)	-	Group number:4	Wald chi2(6)	-	
sigma_u	0			sigma_u	0		
sigma_e	784.51151			sigma_e	1501468.6		
rho	0			rho	0		

In Table 8, for Model 1 according to the z-statistics calculated with resistant standard errors, the effects of operating expenses, internet banking user numbers, mobile banking user numbers, and credit card user numbers on the number of employees are insignificant. For Model 2, according to the z-statistics calculated with resistant standard errors, the effects of internet banking user numbers, mobile banking user numbers, and POS user numbers on operating expenses are significant.

5. CONCLUSION

The Turkish banking system is currently undergoing a digital transformation phase associated with the development of a customer-centric ecosystem. The banks included in our research are providing services to their customers through the digital transformation brought about by Industry 4.0. The digitalization in the banking system has had a positive impact on the sector's economic indicators, while also contributing to an increase in the number of customers. Furthermore, due to the decline in the number of branches and personnel performing banking operations under the traditional business model, financial savings have also been observed. In fact, banks aim to operate with a minimum number of personnel and branches, redirecting their growing profitability towards technology tools shaped by the demands of next-generation banking customers, as well as investing in their own R&D activities.

In this study, Model 1 tests the relationship between the number of personnel as the dependent variable and the following independent variables: operating expenses, number of internet banking users, number of mobile banking users, number of customers, number of credit card users, number of ATMs, and number of POS terminals.

In Model 2, the relationship is tested between operating expenses as the dependent variable and the following independent variables: number of internet banking users, number of mobile banking users, number of customers, number of credit card users, number of ATMs, and number of POS terminals.

As a result of the cross-sectional dependence test conducted in Model 1, cross-sectional dependence was detected, and the slope coefficients were found to be homogeneous. The results of the unit root tests indicate that the series is stationary.

According to the results of Hausman (1979), The Random Effects Model is found to be appropriate for Model 1. In the random effects model, the presence of heteroskedasticity was tested using the Breusch-Pagan Lagrange Multiplier (LM) test, as well as the tests developed by Levene (1960) and Brown and Forsythe (1974). The presence of autocorrelation was tested using the Durbin-Watson (DW) test proposed by Bhargava et. al. (1982), and the locally best invariant tests developed by Baltagi and Wu (1999). For Model 1, the existence of both heteroskedasticity and autocorrelation is confirmed. e Maximum Likelihood Estimator indicates that the relationships between the number of personnel and the following variables operating expenses, number of internet banking users, number of mobile banking users, and number of credit card users are not statistically significant. In contrast, the relationships with the number of customers, number of ATMs, and number of POS terminals are statistically significant. The Generalized Least Squares (GLS) method assumes the core condition of the random effects model: **corr(u_i, x_β) = 0**, which means “there is no correlation between the unit effects and the independent variables.” According to the Z-statistics, the relationships between the number of personnel and operating expenses, internet banking users, mobile banking users, and credit card users are not significant. However, the relationships with the number of customers, number of ATMs, and number of POS terminals are significant. The Random Effects Generalized Estimating Equations (GEE) Population-Averaged Model was also used for testing. The results are consistent with those obtained from the Maximum Likelihood method and are also very close to those of the Generalized Least Squares method. According to the robust standard errors calculated using the estimators of Huber, Eicker, and White, the effects of operating expenses, internet banking users, mobile banking users, and credit card users on personnel expenses are not statistically significant. However, the relationships between personnel expenses and the number of customers, ATMs, and POS terminals are statistically significant.

In Model 2, as a result of the cross-sectional dependence test, cross-sectional dependence was detected, and the slope coefficients were found to be homogeneous. The results of the unit root tests indicate that the series is stationary.

When the Hausman (1979) test is applied, the Random Effects Model is found to be appropriate. In the random effects model, the presence of heteroskedasticity is tested using the Breusch-Pagan Lagrange Multiplier (LM) test, as well as the tests developed by Levene (1960), and Brown and Forsythe (1974). The presence of autocorrelation is tested using the Durbin-Watson (DW) test developed by Bhargava et. al. (1982) and the locally best invariant tests by Baltagi and Wu (1999). For Model 2, the presence of both heteroskedasticity and autocorrelation is accepted. The Maximum Likelihood Estimator indicates that the relationships between operating expenses and internet banking, mobile banking, and the number of credit cards are statistically significant. On the other hand, the relationships with the number of customers, ATMs, and POS terminals are not significant. The Generalized Least Squares (GLS) method assumes the core condition of the random effects model, **corr(u_i, x_β) = 0**, meaning “there is no correlation between unit effects and independent variables.” According to the Z-statistics, the relationships between operating expenses and the number of internet banking users, mobile banking users, and credit card users are significant. In contrast, the relationships with the number of POS terminals and customers are significant, while the relationship with the number of ATMs is not. The Random Effects Generalized Estimating Equations (GEE) Population-Averaged Model was also used for testing. The results are consistent with those obtained from the Maximum Likelihood Estimator and are also very close to those of the Generalized Least Squares method. According to the Z-statistics calculated using robust standard errors based on the estimators of Huber, Eicker, and White, the number of internet banking users, mobile banking users, and POS terminals have a statistically significant effect on operating expenses. However, the relationships between operating expenses and the number of customers, ATMs, and credit card users are not statistically significant.

For Model 1, the relationship between the dependent variable, number of personnel, and the independent variables operating expenses, number of internet banking users, number of mobile banking users, and number of credit card users was found to be insignificant in all the tests conducted. However, the relationships with the number of customers, number of ATMs, and number of POS terminals were negative and significant. The significant relationship between the number of personnel and the number of customers suggests that the increase in customer numbers corresponds to traditional banking practices, which Musaev et al. (2020) refer to as Banking 1.0. A small portion of bank customers still prefer traditional banking services. However, the majority of the new customer profile prefers digital banking. Moreover, according to Musaev et al. (2020), the significant relationship between the number of personnel and the number of ATMs corresponds to Banking 2.0, while the relationship with the number of POS terminals corresponds to Banking 3.0.

For Model 2, there is a significant positive relationship between the dependent variable, operating expenses, and the independent variables: number of internet banking users, number of mobile banking users, and number of POS terminals. The relationships between operating expenses and the number of customers, ATMs, and credit card users are insignificant. According to Musaev et al. (2020), the variables with significant relationships to operating expenses—internet banking users, mobile banking users, and POS terminals correspond to Banking 3.0 and Banking 4.0. The independent variables that show significant relationships with the dependent variable in Model 1, which is the number of personnel, correspond to Banking 1.0 and Banking 2.0, while those with insignificant and negative relationships correspond to Banking 3.0 and Banking 4.0, indicating a substitution effect through technology. For Model 2, the independent variables that have significant relationships with operating expenses correspond to Banking 3.0 and Banking 4.0, while the ATM count, which shows an insignificant relationship, corresponds to Banking 2.0. The correlation between technological investments in the banking sector and technological developments is very clear. Between 2009 and 2020, while the number of personnel increased on average by 21.66%, operating expenses, internet banking users, mobile banking users, credit card users, ATMs, and POS terminals increased on average by 400.64%. Additionally, assets, equity, loans, and deposits increased on average by 246.85%, customer numbers increased by 81.75%, and net profit increased by 96.21%. This clearly shows that the demands of the new-generation customer ecosystem favor digital banking. The Banks are heavily investing in customer demands and the new generation technologies brought by Industry 4.0, developing applications in their IT and R&D departments to achieve digital transformation. The average increase of 21.66% in personnel employment about 1.8% annually over 12 years in our research topic indicates that traditional banking will become completely obsolete in the near future.

For a developing country like ours, with a young population, the banking sector is one of the most important employment areas. However, this research shows us that the banking sector is rapidly digitalizing in accordance with Moore's Law, which has enabled them to achieve significant profitability in recent years. It is clear that banking employees will face serious concerns regarding job security in the near future due to the sector’s digital transformation. Moreover, it is evident that the employment demands of university students aiming for a career in banking will not be met. The primary goal of this thesis is to raise awareness among current sector employees and students aspiring to build a career in banking about this impending risk.

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