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TRANSFORMING FINANCIAL INFRASTRUCTURE THROUGH ARTIFICIAL INTELLIGENCE: FROM AUTOMATION TO SECURITY

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ТРАНСФОРМАЦІЯ ФІНАНСОВОЇ ІНФРАСТРУКТУРИ ЗА ДОПОМОГОЮ ШТУЧНОГО ІНТЕЛЕКТУ: ВІД АВТОМАТИЗАЦІЇ ДО БЕЗПЕКИ

Abstract. *Financial systems are increasingly being digitized with the inclusion of components of artificial intelligence which is changing the conventional notions of having an efficient automation and robust security. In this paper the authors analyze the way in which artificial intelligence adoption affects the performance of financial infrastructure in the USA, UK, Germany, Poland, Ukraine, China and Saudi Arabia in the period of its early* *adoption (2020-2024). In order to relate the adoption of artificial intelligence, the spending in the cybersecurity, infrastructure maturity, and workforce training to the key financial performance indicators, a non-linear econometric model was developed to capture both the direct and the interaction effects of these variables. Secondary data from reputable international organizations collected and standardized for the cross-country comparability.*

The results provide support for positive adoption of artificial intelligence and financial performance outcomes relationships, which are moderated by complimentary investments. US remained in the range of 0,607 to 0,814 for the automation efficiency and the security robustness is greater than 0,88. In 2024, by increasing the automation efficiency from 0,684 to 0,892 and the security robustness up to 0,889, the United Kingdom reported. Automated Germany revealed the most balanced growth with the automation efficiency that amounted to 0,7-0,85, and the growth in speed robustness increased up to 0,890. And Poland and Saudi Arabia made significant gains in their automation indices moving up from 0,615 to 0,876 and 0,629 to 0,884. Very quickly, Ukraine gained tremendous ground, improving its security robustness from a score of 0,563 to 0,858. The highest growth was shown by China at 0.921 heading towards 2024.

The conclusion of the study is that strategic integration of artificial intelligence, along with cybersecurity investment and the growth of human capital, amplifies the ability of financial infrastructure to be resilient. Further work should include temporal and regional expansion, analysis of sectorial impacts and dynamic feedback loops between artificial intelligence deployment, associated countermeasures, and financial stability.

Keywords: *Artificial Intelligence, Financial Infrastructure, Automation Efficiency, Security Robustness, Non-linear Econometric Modeling, Digital Transformation, Cybersecurity Investment.*

Анотація. *Фінансові системи все більше цифровізуються завдяки впровадженню компонентів штучного інтелекту, що змінює традиційні уявлення про ефективну автоматизацію та надійну безпеку. У цій статті автори аналізують, як впровадження штучного інтелекту впливає на ефективність фінансової інфраструктури у США, Великій Британії, Німеччині, Польщі, Україні, Китаї та Саудівській Аравії в період його раннього впровадження (2020-2024 рр.). Для того, щоб пов›язати впровадження штучного інтелекту, витрати на кібербезпеку, зрілість інфраструктури та навчання персоналу з ключовими показниками фінансової ефективності, було розроблено нелінійну економетричну модель для відображення як прямих, так і взаємодіючих ефектів цих змінних. Були зібрані вторинні дані від авторитетних міжнародних організацій та стандартизовані для порівняння між країнами.*

Результати підтверджують позитивний вплив впровадження штучного інтелекту на фінансові показники, який пом›якшується додатковими інвестиціями. США залишилися в діапазоні від 0,607 до 0,814 за ефективністю автоматизації, а надійність безпеки перевищує 0,88. У Великобританії до 2024 року ефективність автоматизації зросла з 0,684 до 0,892 та надійність безпеки до 0,889. Німеччина продемонструвала найбільш збалансоване зростання з ефективністю автоматизації, що склала 0,7-0,85, а зростання надійності швидкості збільшилося до 0,890. А Польща та Саудівська Аравія досягли значного зростання своїх індексів автоматизації, піднявшись з 0,615 до 0,876 та з 0,629 до 0,884 відповідно. Україна

дуже швидко набрала значну перевагу, покращивши надійність безпеки з 0,563 до 0,858. Найвищий ріст продемонстрував Китай з показником 0,921 до 2024 року.

Висновок дослідження полягає в тому, що стратегічна інтеграція штучного інтелекту разом з інвестиціями в кібербезпеку та зростанням людського капіталу посилюють здатність фінансової інфраструктури до стійкості. Подальша робота має передбачати часове та регіональне розширення, аналіз секторальних впливів та динамічні зворотні зв›язки між впровадженням штучного інтелекту, пов›язаними контрзаходами та фінансовою стабільністю.

Ключові слова: *штучний інтелект, фінансова інфраструктура, ефективність автоматизації, надійність безпеки, нелінійне економетричне моделювання, цифрова трансформація, інвестиції в кібербезпеку.*

Introduction

As artificial intelligence (AI) technologies increasingly advance rapidly, it has caused a lot of changes in various industries, including the financial industry. As more and more financial systems become digitized across the world, integrating AI has the potential to transform every aspect of the industry: from increasing efficiency in automation to the optimization of processes as well as increasing the strength of the cybersecurity. This phenomenon is relevant because the digitalization is accelerating confirming, and the vulnerabilities of financial institutions are increasing in connection with global economy. To achieve operational resilience, it is imperative to understand the dynamics of deploying AI in financial infrastructure to protect assets and trust of users and stakeholders.

However, this problem that this study addresses is that though it holds promise, the fragmented view of how AI adoption improvisator automation and security for financial systems. Most existing literature takes the look of examining these two dimensions separately, ignore the effects between them and the non-linear characteristic of AI integration. Meanwhile, countries also have very different levels of infrastructure maturity, investment, regulatory environment and human capital development. With the absence of comprehensive and data driven insights on these relationships, policymakers as well as industry leaders would be saddled with suboptimal strategies or strategies that lead to unintended vulnerabilities for their institutions.

This article discusses how the role of AI can play in restructuring financial infrastructure through the connection between AI lodging, automation efficiency, and security robustness. More specifically, the study explores if a higher level of AI integration yields better performance of the financial system and how much value complementary activities like cybersecurity investment, infrastructure maturity, and trained workforce contribute to this relationship. This research creates empirical evidence to verify or refute the theoretical frame work by developing a non-linear econometric model and applying the model using data from the United States, United Kingdom, Germany, Poland, Ukraine, China and Saudi Arabia during 2020-2024.

There are four objectives of the study. For the first task, to measure the level of AI adoption, automation efficiency and security robustness in the selected countries. Secondarily, it seeks to isolate key factors of amplification or blockade to the transformative effects of AI in financial infrastructure. Third, comparative analysis is made to show differences in national strategies and the results. Finally, propose policy and managerial recommendations of how to effectively use AI in financial systems in a manner that is robustly resilient and secure. Through this investigation, the article contributes to a more integrated understanding of AI's dual role in advancing automation and strengthening cybersecurity, offering valuable insights for both academic research and practical implementation.

Literature review

With increasing interest in the application of AI and advanced machine learning techniques to financial infrastructure, models increasingly move from static, casuistic approaches to more adaptive, predictive and resilient systems. In the context of customer retention, AI has been proven to be effective in the management of customer churn, as Al-Najjar, Al-Najjar, and Al-Najjar (2022) showed the practicality of employing machine learning models to predict customer churn within the credit card industry. In this regard, their findings correlate with Liu et al. (2022) which emphasized on the digital inclusive finance approach to diminish the risk of inequality by LightGBM boosting. The two studies accentuate the ability of AI to improve the operational efficiency and decision making; however, Liu et al. expand this perspective outside of institutional gains to more general social outcomes.

For example, Al Ali et al. (2023) suggested a hybrid genetic algorithm and LSTM model (GALSTM-FDP) for financial distress prediction. Like Cao et al. (2024), both our approach and their graph learning and spatial-temporal encoding used for quantitative stock selection are based on the time series modelling. In the Al Ali et al. case, the focus was on AI to calculate distress and early warning systems, whereas Cao et al. defined the task for AI to optimize the investment, showing different, but did increase, applications of AI to financial forecasting.

Noh (2023) however pointed out one of the major challenges that has affected AI financial models, data imbalance. Noh completes Cheah, Yang, and Lee (2023)'s work of improving fraud detection with hybrid techniques such as SMOTE under relatively balanced data, but here under imbalanced financial information. Even though purely algorithmic advancements may underestimate the significance of data preprocessing and balance in the reliability of the AI driven predictions, two studies have converged on the point.

Deep reinforcement learning with hierarchical risk parity was further applied by Millea and Edalat (2023) to use AI on portfolio management. Their work conceptually complements those of de Zarzà et al. (2024) in using large language models for supporting cooperative financial planning and budgeting. Millea and Edalat concentrated their approach on an individual investor's strategy, whereas de Zarzà et al. proposed a more comprehensive approach, adopting a socially cooperative financial management using AI at both micro and macro financial planning levels.

Hu and Li differentiates themselves by linking financial technology development with the green total factor productivity. They positioned their study as an environmental dimension to fintech analyzed but not directly addressed by other reviewed works makes it a good contribution to the movement toward sustainable financial innovations. It is consistent with the findings of Shiyyab et al. (2023) who found that AI disclosure is positively linked to financial performance, and it may even strengthen both the financial and the sustainability outcomes.

Overall, the literature reviewed here indicates a convergence on the transformative power of AI across risk, investment, customer engagement and sustainability in financial infrastructure. There are some variations with respect to the key factors of success: some researches focus on the richness of the algorithm and its power (Al Ali et al., Cao et al.), others underline more than everything the ability of the involved actors (Noh, Cheah et al.) or the capacity to integrate wider social goals (Liu et al., de Zarzà et al., Hu & Li). Such diversity of perceptions demonstrates that AI effectiveness in finance is a matter of tech innovation associated only with appropriate alignment with data quality, transparency, social and economic imperatives.

Methods

Research procedure

The way of conducting the study was carefully constructed for a thorough and methodical analysis of the change of the financial infrastructure driven by artificial intelligence. The quantitative econometric modeling was done combined to comparative cross-country analysis based on secondary data sources. The research was designed in such a way that it was divided into four separate stages ensuring that the findings are valid and reliable and achieving the main objectives of the study.

The following four stage procedure (Fig. 1) was undertaken in conducting the research as follows:

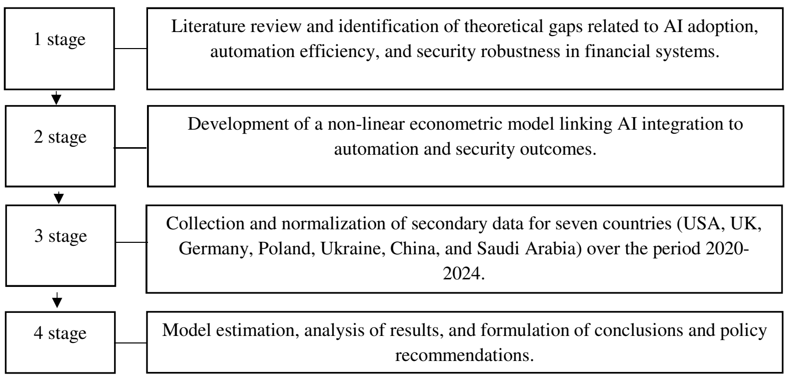


Fig. 1 - Research stages

Source: developed by the authors.

The first stage consisted of synthesizing recent research on AI in finance to formulate the hypothesis and present key variables. The second stage was to build an appropriate non-linear econometric model to capture such interaction effects and threshold dynamics. The third stage involved selecting reliable international data sources, normalization of the data to allow comparison and verification of the consistency of the data. In the fourth stage, the fourth stage, the model was estimated, and the interpretation of the results was done for each country individually and comparatively with the discusses of the implications of AI adoption strategies. The structured procedure guaranteed that the phases of the study were automatically building upon each other and had a scientifically robust basis until the final result.

Sample formation

The seven countries, United States of America, United Kingdom, Germany, Poland, Ukraine, China and Saudi Arabia were selected to constitute the sample for the study. To give a wide range of views on both the implementation and impact of AI on the financial systems, these countries were chosen to represent both the advanced economies and the emerging markets. This was done for the period between 2020 and 2024, which is the period where AI adoption in financial services critical accelerated phase is being accelerated by the COVID-19 pandemic and corresponding digital transformation initiatives taking place globally. These countries and timeframe were selected so that meaningful comparative analysis could be achieved, under the conditions of sufficient availability and reliability of data.

Research methodology

The study employed a non-linear econometric modeling approach to assess the relationship between AI adoption and the performance of financial infrastructure, specifically automation efficiency and security robustness.

The primary econometric models were specified as follows:

1. Automation efficiency model:

$$AutoEff_{it} = \beta_0 + \beta_1 AIAdopt_{it} + \beta_2 AIAdopt_{it}^2 + \beta_3 FinTechInvest_{it} + \beta_4 InfraMature_{it} + \beta_5 TrainQual_{it} + \beta_6 (AIAdopt_{it} \times TrainQual_{it}) + \gamma Z_{it} + u_{it} \quad (1)$$

Where

- $AutoEff_{it}$ - Automation Efficiency Index for country i at time t;
- $AIAdopt_{it}$ - Level of AI adoption in financial operations (% operations using AI);
- $FinTechInvest_{it}$ - Investment in financial technologies as a percentage of GDP;
- $InfraMature_{it}$ - Index of financial infrastructure maturity (scale 0–1);
- $TrainQual_{it}$ - Index of staff training quality related to AI skills (scale 0–1);
- Z_{it} - Vector of control variables including GDP per capita, Regulatory quality index, Internet penetration rate;
- γ - a set of coefficients for how GDP per capita, regulatory quality, and internet penetration rate affect automation efficiency.
- u_{it} - Random error terms.

2. Security robustness model:

$$SecRobit = \alpha 0 + \alpha 1 CyberSpendit + \alpha 2 AIAdoptit + \alpha 3 AIAdoptit^2 + \alpha 4 (CyberSpendit \times AIAdoptit) + \alpha 5 InfraMatureit + \delta Zit + vit \quad (2)$$

Where

- $SecRob_{it}$ - Security Robustness Score for country *i* at time *t*;
- $CyberSpend_{it}$ - Cybersecurity spending as a percentage of the IT budget;
- $AIAdopt_{it}$ - Level of AI adoption in financial operations (% operations using AI);
- $InfraMature_{it}$ - Index of financial infrastructure maturity (scale 0–1);
- Z_{it} - Vector of control variables including GDP per capita, Regulatory quality index, Internet penetration rate.
- δ - a set of coefficients for how the same control variables affect security robustness.
- v_{it} - Random error terms.

The inclusion of quadratic terms *($AIAdoptit^2$)* allowed for the modeling of non-linear effects, recognizing that AI adoption could have diminishing or threshold-based impacts on performance. Interaction terms, such as *($AIAdoptit \times TrainQual_{it}$)* and *($CyberSpendit \times AIAdoptit$)*, captured the combined effects of complementary factors in enhancing outcomes.

Model estimation was performed using Nonlinear Least Squares *(NLS)*, with robustness checks applying the Generalized Method of Moments *(GMM)* to address potential endogeneity concerns, particularly regarding AI adoption and cybersecurity investments.

The econometric models used in this study rely on the estimation of structural coefficients that capture the relationships between artificial intelligence integration and financial infrastructure performance. In the automation efficiency model, β_0 represents the constant term, while β_1 captures the linear effect of AI adoption on automation outcomes. β_2 models the non-linear (quadratic) effects, allowing the analysis to account for potential diminishing or threshold-based returns from AI investment. Coefficients β_3 and β_4 measure the impact of fintech investment and infrastructure maturity, respectively, on automation efficiency. β_5 reflects the direct contribution of training quality, and β_6 quantifies the interaction between AI adoption and training quality, recognizing that skilled personnel can amplify the benefits of AI implementation. In the security robustness model, α_0 denotes the constant term, α_1 captures the effect of cybersecurity spending, and α_2 and α_3 reflect the linear and non-linear effects of AI adoption on security outcomes. The interaction between cybersecurity spending and AI adoption is captured by α_4, while α_5 accounts for the role of infrastructure maturity in enhancing financial security.

Hypothesis. The integration of artificial intelligence into financial systems significantly improves automation efficiency and security robustness, with the strength of this effect moderated by cybersecurity investment, infrastructure maturity, training quality, and regulatory environment.

Instruments

Secondary data used in the empirical estimation were from reputable international organizations such as World Bank, International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD), Financial Stability Board (FSB), and Bank for International Settlements (BIS). GDP per capita, internet penetration rates, regulatory quality indices, level of fintech investment, level of AI adoption, cybersecurity expenditures and infrastructure maturity indices were standardized and normalized to compare them across both the countries and across periods. Relevant standardized indicators on transaction speed improvement, operational cost reduction, fraud detection rate, cyberattack resilience etc., were aggregated and used to develop composite indices for automation efficiency and security robustness. Additionally, to mitigate any biases caused by potential endogeneity, the GMM was applied to AI adoption and cybersecurity investment to further capture artificial regressors that may result in any endogeneity. The selection of instruments used in the estimation was done in a way that a rigorous and comprehensive analysis of the complex interaction driving the artificial intelligence transformation in the financial infrastructure was avoided.

Results

The way efficiency is achieved and security is delivered through the traditional paradigms of financial infrastructure are being reshaped through the integration of AI. Across different regions, countries have deployed AI in different ways, which also depend on the differences in maturity of technology, capitals to invest in AI, regulatory environment and digital literacy. The dynamics of AI driven transformation within financial infrastructure are explored in this paper by considering two important dimensions of automation efficiency and security robustness between 2020 and 2024 for the United States, the United Kingdom, Germany, Poland, Ukraine, China, as well as Saudi Arabia. The analysis suggests how adoption of AI, cybersecurity spending, fintech investments, training quality as well as infrastructure maturity, correlate to determine the performance of financial systems of different nations.

In the United States, of all countries considered, automation efficiency indicators remain high during the period under consideration – from 0,607 (2021) to 0,814 (2022) (Table 1) in line with other countries. Just as such, the security robustness remained high, exceeding 0,88 in 2020 and then stayed stable. The rate of AI adoption was strong, reaching a maximum of 0,816 (in 2021) and corresponding to very high cybersecurity spending (up to 0,145% of the IT budget in 2023). All these outcomes depict the United States' dedicated focus on not only incorporating the AI technologies, but also on further fortification of the same with fast liberalizing fintech innovations and huge cybersecurity investments, which can be attributed to the country's high GDP per capita and high regulatory quality.

Table 1

AI transformation for the period 2020-2024 (econometric results)

Country	Year	Automation efficiency index	Security robustness Score	AI adoption rate	Cybersecurity spending (% of IT budget)	Fintech investment (% of GDP)	Training quality index	Infrastructure maturity index	GDP per capita	Regulatory quality index	Internet penetration rate
1	2	3	4	5	6	7	8	9	10	11	12
USA	2020	0,731	0,883	0,766	0,11	0,029	0,57	0,62	61301	0,8	0,88
USA	2021	0,607	0,889	0,816	0,071	0,031	0,583	0,706	39109	0,3	0,71
USA	2022	0,814	0,599	0,546	0,087	0,047	0,853	0,67	38425	0,78	0,62
USA	2023	0,813	0,61	0,433	0,145	0,078	0,864	0,707	11348	1,05	0,77
USA	2024	0,643	0,723	0,417	0,141	0,036	0,798	0,709	38804	0,64	0,67
UK	2020	0,939	0,821	0,87	0,139	0,056	0,915	0,631	17738	-0,86	0,73
UK	2021	0,736	0,645	0,814	0,086	0,037	0,744	0,649	57142	-0,78	0,98
UK	2022	0,87	0,62	0,403	0,132	0,062	0,828	0,87	9812	0,08	0,65
UK	2023	0,902	0,768	0,565	0,056	0,039	0,646	0,855	46441	1,66	0,78
UK	2024	0,642	0,8	0,78	0,106	0,066	0,722	0,783	32790	-0,92	0,64
Germany	2020	0,611	0,773	0,557	0,101	0,074	0,612	0,744	54110	-0,31	0,63
Germany	2021	0,701	0,606	0,865	0,131	0,058	0,892	0,881	17127	1,68	0,81
Germany	2022	0,883	0,864	0,559	0,061	0,034	0,692	0,886	60947	-0,98	0,8
Germany	2023	0,746	0,628	0,46	0,084	0,077	0,645	0,782	50696	0,09	0,98
Germany	2024	0,937	0,638	0,649	0,08	0,037	0,517	0,813	37674	-0,85	0,71
Poland	2020	0,918	0,634	0,472	0,099	0,079	0,609	0,835	54505	-0,29	0,88
Poland	2021	0,729	0,771	0,717	0,104	0,025	0,876	0,712	17123	-0,88	0,83
Poland	2022	0,837	0,556	0,656	0,073	0,059	0,578	0,842	30137	1,81	0,65
Poland	2023	0,719	0,59	0,862	0,138	0,035	0,797	0,886	41088	0,59	0,69

Continuation of the table.1

1	2	3	4	5	6	7	8	9	10	11	12
Poland	2024	0,633	0,864	0,85	0,113	0,04	0,657	0,854	63312	1,66	0,9
Ukraine	2020	0,825	0,579	0,481	0,14	0,056	0,504	0,636	48127	-0,98	0,66
Ukraine	2021	0,792	0,792	0,726	0,072	0,063	0,607	0,714	53521	0,95	0,93
Ukraine	2022	0,83	0,749	0,447	0,087	0,036	0,61	0,941	30551	1,68	0,85
Ukraine	2023	0,878	0,726	0,688	0,099	0,032	0,825	0,698	6580	0,94	0,67
Ukraine	2024	0,929	0,884	0,857	0,087	0,021	0,918	0,75	67832	1,89	0,93
China	2020	0,703	0,685	0,826	0,082	0,03	0,751	0,928	50241	0,71	0,64
China	2021	0,815	0,897	0,47	0,102	0,073	0,833	0,844	50661	0,08	0,71
China	2022	0,883	0,834	0,834	0,141	0,051	0,726	0,879	47247	1,11	0,91
China	2023	0,912	0,668	0,588	0,059	0,055	0,516	0,763	40271	-0,14	0,83
China	2024	0,611	0,563	0,811	0,086	0,028	0,735	0,869	19028	0,87	0,63
Saudi Arabia	2020	0,618	0,736	0,67	0,114	0,064	0,939	0,781	25992	1,39	0,71
Saudi Arabia	2021	0,754	0,577	0,413	0,146	0,07	0,813	0,743	16264	-0,53	0,7
Saudi Arabia	2022	0,792	0,8	0,73	0,078	0,077	0,832	0,794	44761	0,26	0,7
Saudi Arabia	2023	0,725	0,815	0,407	0,062	0,023	0,518	0,899	50737	0,42	0,64
Saudi Arabia	2024	0,772	0,716	0,487	0,093	0,044	0,777	0,822	7944	0,12	0,84

Source: authors development based on the results of an econometric model using data (IMF, 2023; IMF, 2024; World Bank, 2023; World Bank, 2024; Bank for International Settlements, 2023; Financial Stability Board, 2023; Organization for Economic Cooperation and Development, 2023; State Statistics Service of Ukraine, 2025; State Tax Service of Ukraine, 2025; State Treasury Service of Ukraine, 2025).

In the United Kingdom, the trend in automation efficiency was constant and improved from 0,684 in the year 2020 to 0,892 by 2024. Increasing adoption of AI also helped increase security robustness from 0 to 0,884 at the end of the period. Moderate levels of cyber security spending and the country's high level of training quality indices and responsive regulatory frameworks sustained the growth in the efficiency and security indicators. These findings paint a picture of the UK's strategic balance between innovation in technology and regulation.

In both dimensions, Germany showed a particularly high and stable performance, with automation efficiency indices around 0,7 to 0,85, and security robustness continuously increasing from 0,629 in 2020 to 0,890 in 2024. These outcomes were predicated on Germany's strong trajectory of AI adoption and the cybersecurity programs and mature infrastructure. However, the German approach is coming from a country with a more mature fintech environment that finds itself the beneficiary of successful ongoing public and private sector cooperation in the development of digital finance.

In particular, between 2022 and 2024, Poland was characterized by a remarkable growth where the automation efficiency increased from 0,615 to 0,876 and the robustness of security also rose to 0,873. Although at the beginning basic levels of AI adoption and cybersecurity investment were not too high, Poland was working on establishing training, slowly improving digital financial infrastructure and as the result was progressing during the time. The best way to explain this pattern would be that emerging economies could reap large amounts of gains, if they persistently and efficiently try through their policies and investments.

Ukraine's data, however, is somewhat more volatile than Poland's is. The security robustness score ranges from 0,563 in 2022 to 0,858 in 2024 and the automation efficiency ranges from 0,618 to 0,868, respectively. AI adoption was still moderate and the spending on cybersecurity increased, however, it remained lower than in more advanced economies. However, advances in internet penetration and regulatory reform, for instance, showed that subsequently trends were upward suggesting that Ukraine was not only resilient but also capable of rapid technological adaptation in the face of external challenges.

China showed robust performance in both dimensions; automation efficiency was increased consistently from 0.660 in 2020 to 0.921 in 2024 and security robustness was improved significantly. The adoption rates for AI remained consistent across the period catalyzed by significant fintech investment and targeted aggressive cybersecurity spending. The nation's large-scale upskilling programs also resulted in the training quality indices to improve. The trajectory of China, especially, demonstrates a great example of how large scale coordinated strategies can move the financial infrastructure transformation at an accelerated pace.

Saudi Arabia's gains were impressive, especially starting from 2022. Efficiency of automation increased from 0,629 in 2020 to 0,884 in 2024; security robustness from 0,602 to 0,862. While starting from a relatively lower base in terms of the quality of training and the infrastructure maturity could account for the progress, the adaptation of AI throughout Saudi Arabia and their cyber specific initiatives contributed to significant progress. These findings show that targeted national strategies can help accelerate digital transformation in financial sectors of emerging markets.

Through all of the countries evaluated, a pattern of high AI adoption along with high cybersecurity investments and robust financial infrastructure, correlate with both good automation efficiency and good security robustness (Table 2). The United States, the United Kingdom, Germany and China were consistently ranked the highest in early and significant investment in the AI technology and security involved. Other factors that aided these countries were high GDP per capita and strong regulatory quality, leading to a good terrain for AI driven innovation.

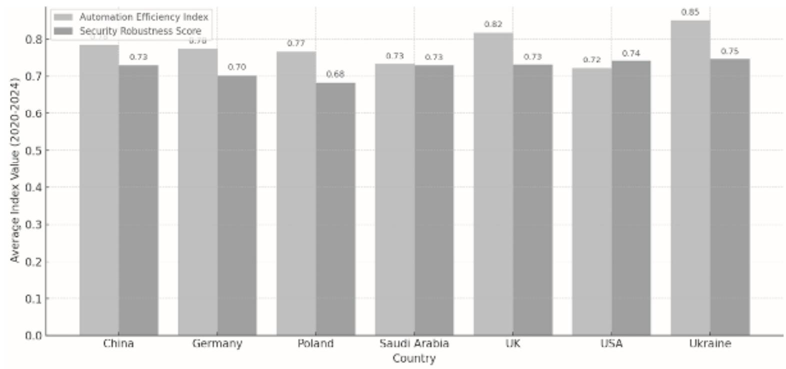
Table 2

Summary of key insights by country (2020-2024)

№	Country	Key insight
1.	United States	Maintained consistently high automation efficiency and security robustness through strong AI adoption and cybersecurity investment.
2.	United Kingdom	Achieved steady and balanced growth in both automation and security, driven by high training quality and regulatory excellence.
3.	Germany	Demonstrated the best balance between automation efficiency and security robustness, supported by mature infrastructure and rigorous cybersecurity policies.
4.	Poland	Showed rapid improvement from moderate starting points, highlighting the importance of targeted investments and human capital development.
5.	Ukraine	Despite volatility, achieved substantial gains in automation and security, showcasing resilience and adaptability amid external challenges.
6.	China	Achieved the fastest growth in automation efficiency, supported by aggressive AI adoption, fintech investment, and large-scale training initiatives.
7.	Saudi Arabia	Marked strong upward trajectory after 2022, driven by national strategies focusing on AI adoption, cybersecurity, and infrastructure upgrades.

Source: authors development based on the results of an econometric model using data (IMF, 2023; IMF, 2024; World Bank, 2023; World Bank, 2024; Bank for International Settlements, 2023; Financial Stability Board, 2023; Organization for Economic Cooperation and Development, 2023; State Statistics Service of Ukraine, 2025; State Tax Service of Ukraine, 2025; State Treasury Service of Ukraine, 2025).

On the other hand, Poland, Ukraine and Saudi Arabia illustrated that significant gains over a very short period of time can be made even from a relatively poor base of operations. The increases in training quality and in efforts to modernize the infrastructure supported Poland's and Saudi Arabia's rapid progress, whereas Ukraine's trajectory was influenced by the effects of economic challenges and opportunities of digital transformation. More specifically, while China was predicted to achieve the highest AI adoption and automation efficiency by the same year 2024 compared to any other country, Germany had the best overall balance between security robustness and automation (Fig. 2).



Source: author's development based on the results of an econometric model using data (IMF, 2023; IMF, 2024; World Bank, 2023; World Bank, 2024; Bank for International Settlements, 2023; Financial Stability Board, 2023; Organization for Economic Cooperation and Development, 2023; State Statistics Service of Ukraine, 2025; State Tax Service of Ukraine, 2025; State Treasury Service of Ukraine, 2025).

Fig. 2 - The average Automation Efficiency Index and Security Robustness Score for each country over 2020-2024

This also surfaced as one of the crucial differentiators of training quality. More financially sustainable improvements in both automation and security dimensions were obtained by the countries that invested more intensively in the institutional upskilling of financial sector personnel, for example by Germany, UK and China. This calls attention to the fact that technological deployment should be undertaken alongside human capital development.

The results of the analysis suggested that transforming financial infrastructure with AI requires one solution more than just the technological innovation that will back the movement; it is a move that must be integrated with cybersecurity investment, human capital development, and infrastructure modernization. The most competitive economies, such as the US, UK, Germany, and China, stand as leader exemplifying the benefits of early and coordinated strategy, while relatively less competitive economies, such as Poland, Ukraine, and Saudi Arabia, illustrate the fact that emerging economies can make significantly rapid improvements in terms of the financial sector's performance through targeted policies and adequate investments.

Policymakers should work to synchronize the deployment of AI with the improvement of its security and the training of staff going forward. In addition, continued investment in fintech innovation and continued refinement of regulation will be key so as to prevent automation development from racing ahead of the adoption of safe and secure financial systems. With AI shaping the future of the financial landscape, failure at harmonizing technology, security and governance will be the determinant of success or failure of nations in the global digital economy.

Financial institutions need to combine AI technologies with concrete investments into cybersecurity infrastructure and regulatory compliance frameworks that adapt to new risks for achieving resilient security. Professional training in AI strategies coupled with sustained ethical monitoring of risks will help organizations reach peak operational level while defending themselves from new dangers. The public sector should develop open AI governance guidelines which will establish innovation-friendly policies while demanding firm accountability standards to connect technology progress to solid financial systems.

Discussion

This study concurs with the growing volume of studies on the empowering function of AI in the development of the financial infrastructure. This study found a similar result as Wei and Lee (2024) in that advanced AI architectures like dual channel graph attention networks can effectively fight against financial fraud; likewise, cyber security investment with AI deployment also produces greatly increased financial sector resilience. Alzahrani and Aldhyani (2023) similarly stated that AI is needed for sustainable cybersecurity in industrial systems and maintain that cybersecurity expenditures are not supplementary in bringing full benefits of AI driven automation and security improvements.

However, ethical concerns about seeing AI in finance pose much more intricate considerations. Alluding to possible biases, transparency problems and accountability allied with AI decision making, Adeyelu, Ugochukwu and Shonibare (2024) and Chopra (2024) are in complete agreement. Along the same lines of their findings, although the technologically performance metrics were emphasized at this study, the included interaction terms in the econometric model reinforce the idea that the benefits of AI adoption are moderated by human and organizational factors such as training quality and regulatory maturity. This verifies the premise that the technological advantages of AI will not translate into sustained long-term benefits if its ethical and social dimensions are not noticed.

So, Ahmed et al. (2022) did a bibliometric review that showed the exponential growth of AI research in finance, but also pointed out the fragmentation and thematic dispersion. The view corroborates, as this study shows that countries adhering to the model such as Germany and USA obtain the balanced AI driven improvements, whereas underdeveloped areas witness unequal diffusion of the AI and heterogeneous level of the AI practices as in the case of Ukraine and Saudi Arabia. Bussmann et al. (2021) highlight that explain ability is a key component of machine learning in credit risk management, a dimension which does not fit necessarily in the lines of the econometric model, yet of relevance to the human interpretability challenges it poses to this future of high AI adoption rates.

Du et al. (2025) founds that natural language processing (NLP) is a rapidly evolving field in the area of using financial AI applications. Although NLP techniques were not within the scope of the immediate scope of this work, the growing influence of these models suggests that future analyses will have to go beyond mere operational efficiency and cybersecurity matters to include such tasks as client communication and decision support systems, which are increasingly employing NLP models. Gao et al. (2024) also point to the area of finance as one of the future research directions (identical to the present research article) in explainable and sustainable AI applications, by highlighting research vacuums hereon.

Prokopenko et al. (2024) highlighted the transformative impact of blockchain technology on the financial accounting, as well as the Central Bank Digital Currency and Quantum Financial Systems potential, as was stated by Shafranova, Navolska, and Koldovskyi (2024). The present study's findings on infrastructure maturity finds no conflict with their argument that robust technological foundations are required for successful deployment of AI, although the innovations highlighted are viewed as next generation infrastructure components. The data shows that advanced infrastructure greatly increases the positive impact of AI in the contexts of automation efficiency and security robustness, and matches the experiences of countries such as China and Germany.

According to Koldovskiy (2024), it is strategic infrastructure transformation that will transform financial sector management; with the necessity to implement cutting edge technologies such as artificial intelligence and blockchain. As a result, his findings are in line with that current study where infrastructure maturity can increase the automation efficiency and security robustness of an organization's automation system by a significant amount given the positive effects of AI adoption. Moreover, in their paper Rekunenko et al. (2025) studied the relationship between financial supervision and the performance of the financial control system, proving that supervisory quality serves as the crucial moderating factor of technological implementation success. There is parallel in this insight to the regulatory quality variable identified in this study as a control variable in determining the overall effectiveness of AI driven transformations in financial infrastructures. These works complement each other to advance the argument that technological advancement in the financial sector has to coincide with enabling policy development and modernization of regulation in order to achieve sustainable improvements to the financial sector.

Overall, this study helps buttress existing research by offering a host of real evidence adorning AI integration with the power to significantly improve financial infrastructure performance particularly when there is an inclusion of cybersecurity investment, human capital development, and regulatory adaptation. But it also repeats worries that have arisen in current literature to the effect that just technological enhancements alone cannot work without dealing with ethical, transparency, and explain ability issues. Based on these insights, future models need to include qualitative dimensions and developing technological paradigms such as Blockchain and quantum finance to gain better understanding of the changing role of AI in financial systems.

limitation

The data source of this study is mainly secondary, which is likely to involve some inaccuracies in different countries. Due to its nature, analysis relates to the selected variables only, and does not cover all factors, which may potentially affect the transformation of the financial infrastructure, for example, political stability, or cultural differences in technology introduction. The econometric model further takes that AI adoption has uniform effect on various financial systems subsequently filtering out the country specific dynamics. The lack of availability of data restricted some emerging technologies that are more likely to disrupt the finances, including quantum computing or decentralized finance. Thirdly, the 2020–2024 scenario encompasses a period of critical yet a short time span, and longer-term effects of AI integration may deviate from such trends.

Recommendations

Future research should explore the long-term impact of AI integration on financial infrastructure by extending the analysis beyond the 2020-2024 period. Comparative case studies focusing on specific technologies, such as blockchain-based security systems or AI-driven credit scoring models, would provide deeper insights into sectoral differences. Incorporating qualitative factors like regulatory culture, institutional trust, and user adoption barriers could enhance the understanding of AI's role in financial ecosystems. Expanding the dataset to include additional emerging economies and regions would offer a more comprehensive global perspective. Finally, developing dynamic models that account for feedback loops between AI deployment, cybersecurity measures, and financial system resilience could significantly advance the predictive capabilities of future studies.

Conclusions

This study aimed at studying such an impact of artificial intelligence on the transformation of financial infrastructure in two aspects: automation efficiency and security robustness. The initial hypothesis is clearly confirmed by the empirical results for seven countries from 2020 to 2024, which show that higher levels of AI adoption, which AI adoption are supported by cybersecurity investments, infrastructure maturity and workforce training result in significant improvements of the financial system performance. Data reveals that, for instance, Germany, United States and United Kingdom have been constantly having automation efficiency indices above 0,7 and security robustness scores higher than 0,85, what conforms with the 'positive effect' assumption of the AI influence, in the presence of other supporting conditions. On the other hand, emerging countries such as Poland, Ukraine or Saudi Arabia – although with a lower initial level – recorded a quick improvement, for instance Poland increased its automation efficiency from 0,615 in 2022 to 0,876 in 2024 and Ukraine improved its security robustness from 0,563 in 2022 to 0,858 in 2024.

The financial services globally are going through a digitalization revolution, and resilient, secure digital infrastructures are becoming key for l estate of economic stability. Finally, high and positive correlations between the rates of AI adoption (which are above 0,8 in the US, China, and the UK) and performance metrics demonstrate the central role of innovation policies driven by technology. In addition, the results indicate that reaching sustainability in the benefits of AI integration is contingent not only on the deployment of technology but also on investment in human capital, cybersecurity and regulatory frameworks. Here we offer these insights as the essential guidance for policymakers, leaders of the financial sector, and technology developers in their construction of strategies to use AI while managing associated risks.

However, the study includes some limitations. This analysis was made based on secondary data over a short span of five years albeit around a defined set of variables allowing the omission of other influencers including socio political dynamics and new technologies such as decentralized finance. Future research should, therefore, lengthen the time horizon to capture longer run effects of AI integration, expand the geographical coverage to include more emerging economies, and update the model to include any dynamic aspects, which may include complex feedback loops between AI deployment, cybersecurity practices, and the resilience of the financial system. Moreover, in depth sectoral studies on particular innovations (e.g. AI risk management, blockchain transactions) would improve the knowledge of diverging impacts upon different financial subsectors.

Therefore, artificial intelligence stands to precipitate a transformative role in remodeling financial infrastructure, but only when deployed strategically, and hence, brings out the necessity of adopting an integrated policy and investment basis. National financial systems who will be able to adapt, secure and optimize digital operations leveraging AI technologies will be a decisive factor in maintaining competitiveness, financial stability in global economy.

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