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Is digital transformation profitable for banks? Evidence from Europe

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A B S T R A C T

Studies on the impact of digital transformation (DT) on bank performance are typically restricted to single countries and present mixed findings. Using data on 279 EU-27 banks from 2017 to 2022 and employing a novel DT index, we demonstrate that DT is associated with higher bank profitability, and that IT and network efficiency are key drivers. Furthermore, Covid-19 and the level of country IT positively moderate this relationship. Interestingly, additional analyses also reveal nonlinear relationships, which suggest that profitability gains from DT investments can take time to materialize and that there are diminishing marginal returns to some DT investments.

1. Introduction

Over the last decade the banking sector has undergone radical digital transformation (DT), reshaping organizational structures, processes and business models (Boot et al., 2021; Kwan et al., 2023). The emergence of digitally native entities such as FinTechs and Neobanks have disrupted traditional banking dynamics, forcing banks to respond through strategic investments to stay competitive (e.g., Boot et al., 2021; Pierri and Timmer, 2022). Covid-19 and evolving regulation have further intensified DT. During Covid-19 EU-27 countries prioritized DT (Savvakis et al., 2024), which, combined with evolving consumer demand, have accelerated the adoption of digital channels as the primary mode of customer engagement (Boot et al., 2021; Kwan et al., 2023), Similarly, new regulations within Europe, including the payment service directive (PSD2), have enabled open banking and helped promote a more competitive and secure banking environment (ECB, 2018).

Although DT is transforming banking, the literature presents inconclusive findings regarding its impact on bank performance. On one hand, investments in DT can positively impact various bank processes and operations, including efficiency and monitoring capabilities (Berg et al., 2020), lending decisions (Pierri and Timmer, 2022; Shang and Niu, 2023), as well as customer base expansion through digital outreach (Kwan et al., 2023). From this perspective, banks' investments in DT may be positive associated with bank performance, as shown by several recent studies. For example, Wu and Cheng (2024) find a positive relationship between DT and bank revenue in China, which strengthens when there are regional policies that promote digitalization. Similarly, Porfírio et al. (2024) study

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the influence of DT on the performance of Portuguese banks using survey data and conclude that DT positively influences business volume and organizational performance. Finally, banks who invest more in DT may realize superior performance during exogenous crises (Dadoukis et al., 2021; Pierri and Timmer, 2022), including during Covid-19 (Dadoukis et al., 2021) and the global financial crisis (Pierri and Timmer, 2022).

On the other hand, while investments in DT can bolster operational efficiencies and customer satisfaction, they may not uniformly translate into improved profitability due to competitive pressures and ongoing cost dynamics (Aral and Weill, 2007); similarly, because traditional communication frictions, historically mitigated by physical branches, persist in certain service domains such as financial advisory and secure transactions (Chiorazzo et al., 2018). Consistent with this, several studies suggest a complex interplay between DT and bank performance. Beccalli (2007) argue for the existence of a "profitability paradox", whereby profitability gains from DT investments are modest in conventional periods. Furthermore, they find that different types of DT investments are associated with positive or negative changes in profitability. Similarly, Xiang and Jiang (2023) uncover a nonlinear relationship between digitalization and Chinese bank performance. Specifically, they find that the impact of digitalization on bank performance matters for small and medium-sized banks but not for large banks.

In this paper, we examine the impact of DT on bank profitability using a novel DT index that considers IT investment levels, process digitalization, and customer acceptance of digital banking channels for a sample of 279 banks from the 27 EU countries (EU-27) from 2017 to 2022. By way of preview, our main findings demonstrate that investments in IT and network efficiency are the two most important DT investments for increasing bank profitability. Moreover, analysis of channels reveals that digital channel development is more positively associated with profitability during Covid-19 pandemic and that a country's digital infrastructure and expertise further positively moderate the relationship between DT drivers and profitability. Additionally, we uncover linear relationships between DT drivers and performance. While sustained IT investments eventually generate significant long-term gains, initial investments may not immediately lead to profitability due to high upfront costs. Similarly, network efficiency exhibits diminishing marginal returns, indicating that after initial optimizations further reductions in physical infrastructure offer limited benefits.

We make several contributions. We extend the recent literature on DT within banking, which typically focuses on single country settings, including the US (Dadoukis et al., 2021; Pierri and Timmer, 2022), China (Liu et al., 2024; Wu and Cheng, 2024) and Portugal (Porfírio et al., 2024) and which presents mixed findings. We expand the geographic focus to the EU, where DT and competition within the banking sector are especially strong and where policy makers are strongly supporting DT. Moreover, we overcome data challenges associated with identifying firms' DT (Beccalli, 2007; Chae et al., 2014) through the construction of a novel DT index. In doing so we provide a clearer, and more generalizable, understanding as to how DT influences bank profitability and the mechanisms through which this relationship manifests. Our findings provide important insights relevant to firms, regulators and policy makers on the role of DT in shaping bank performance in the presence of moderating factors. Specifically, they imply that strategic investments in digital technologies are crucial for banks to enhance operational efficiencies, customer engagement, and overall resilience in a rapidly evolving digital economy.

2. Data and methodology

Our unbalanced panel includes 1516 bank-year observations for 279 EU-27 headquartered banks from 2017 to 2022. We obtain annual consolidated financial from Orbis Bank Focus and macroeconomic variables from the World Bank database to control for possible country effects and require data be available for at least three consecutive years.

2.1. Constructing the digital transformation index

Any study of the role of DT in shaping firm performance is complicated by the absence of structured data on DT in organizations (Beccalli, 2007; Chae et al., 2014). Thus, an important contribution of this paper lies in the development and use of a DT index that integrates financial data with non-financial metrics. This index represents a comprehensive measure of banks' digital channel development and client engagement with these services.

In Appendix Table A1, we identify six distinct variables representing various aspects of a bank's DT efforts (i.e., *PCA inputs*). To reduce the dimensionality of the dataset and identify key patterns, we conducted a principal component analysis (PCA) on these six input variables. First, we identified a comprehensive factor, serving as the DT index, by selecting a single component. Additionally, to investigate the main drivers of DT, we re-ran the PCA and selected several factors according to the Guttman–Kaiser criterion, resulting in three factors. We interpret these factors as measures of "digital channel development," "network efficiency," and "IT investments." A detailed description of these variables and the PCA output is provided in Appendix A.

2.2. Empirical model

To provide empirical evidence of the relationship between bank performance and level of DT, we estimate a series of unbalanced fixed effect panel data regression, defined as follows[1]:

$$Performance_{i,t} = \beta_0 + \beta_1 Digitalisation_{i,t-1} + \beta_2 Control_{i,t-1} + \beta_3 Macro_{j,t-1} + \mu_i + \varepsilon_{i,t-1} \tag{1}$$

[1] For robustness, we also employ the Return of Equity (ROE) as an alternative measure of performance. Results remain qualitatively similar.

where $Performance_{i,t}$ is captured by bank ROA, digitβ_0 is the constant, $Digitalisation_{i,t-1}$ is the DT index (it includes the DT index in the first regression and the three drivers of DT separately), $Control_{i,t-1}$ is a vector of bank-specific control variables, $Macro_{j,t-1}$ represents a vector of macroeconomic variables, μ_i is the unobserved time-invariant individual effect, and $\varepsilon_{i,t-1}$ is the error term, and ***i, j, t*** represent, bank, country, and fiscal year, respectively. The descriptive statistics and variable definitions are presented in Table 1.

3. Empirical results and discussion

3.1. How does IT adoption influence bank performance?

Before analyzing the results of Eq. (1), in Table 2 we present *t*-tests of mean differences between high-IT (those in the top quartile of the DT index distribution) and low-IT banks (those in the lower quartile). The average ROA of high-IT banks (0.890 %) is significantly higher than low-IT banks (0.322 %), which suggests that high-IT banks significantly outperform their low-IT counterparts. Although these are univariate tests, the results are in line with the multivariate results of Wu and Cheng (2024) who find a positive effect of DT on Chinese bank performance, albeit for bank revenue. However, they differ from Xiang and Jiang (2023) who report an average negative impact of DT on Chinese bank ROA. However, Xiang and Jiang (2023) also test and findings a non-linear effect with differences in the relationship between DT and profitability based on bank size.[2]

Banks with higher IT adoption also exhibit better management efficiency, as evidenced by a lower cost-to-income ratio (63.26 compared to 82.86). This over-efficiency appears to stem from cost reduction, with high-IT banks recording lower staff and non-staff expenses. We consider this is broadly consistent with Beccalli (2007), who finds that investments in IT services from external providers positively influence European bank profitability. On the revenue side, enhanced IT adoption enables better “spatial capture” (Boot et al., 2021) and improved ability to serve underserved clienteles (Tang, 2019). Consistent with prior studies (Dadoukis et al., 2021; Berger, 2003), technology in banking appears to be positively associated with cost and lending capacity improvements. Conversely, the lower level of net fees and commissions supports the notion that many fee-generating services are primarily offered through physical branches, such as safekeeping or financial advisory (Chiorazzo et al., 2018). Moreover, high-IT banks exhibit a lower average level of non-performing loans, which reinforces the notion that leveraging digital footprints for consumer lending is crucial for enhancing monitoring capabilities (Berg et al., 2020), and that technology aids in improving lending decisions by facilitating the selection of best borrowers (Pierri and Timmer, 2022).

To shed further light on how DT impacts profitability, Table 3 presents multivariate regressions based on Eq. (1).[3] Column (1) reveals that digitally advanced banks are associated with higher profitability (Dadoukis et al., 2021; DeYoung et al., 2007). Given that various investments in technology could influence bank performance differently (Beccalli, 2007), in columns 2–4 we examine sub-components of the DT index (*digital channel development, network efficiency*, and *IT investments*). We find that the higher profitability of banks that invest more in DT is driven by levels of *IT investments* and by enhanced *network efficiency*. Together these results infer that banks who increase IT investments, to enhance structural efficiency and streamline procedures and processes (largely through cost-reduction measures), are more profitable.

3.2. The moderating effects of COVID-19 and country levels of IT

Since Covid-19 intensified demand for digital services driven by changes in consumers preferences (Wu and Cheng, 2024) and country and EU policy maker objectives (Savvakis et al., 2024), we consider Covid-19 as a potential moderator (Dadoukis et al., 2021; Savvakis et al., 2024). In Table 4 Panel A we construct a dummy, *Post-Covid-19*, which equals 0 before Covid-19 (2017–2020), and 1 post-Covid (2021–2022). We then include this variable and interactions with the *DT index* and each subcomponent.

The results, in Table 4, demonstrate that banks with higher digitalization were more profitable post-Covid. Thus, Covid-19 accelerated digitalization by discouraging in-person interactions and promoting the use of digital channels (Ceylan et al., 2020; Saka et al., 2022). This helps explain why high-IT banks outperformed peers post-Covid-19 (Branzoli et al., 2024; Dadoukis et al., 2021; Kwan et al., 2023). The digital acceleration is likely driven by a need for banks stay competitive—faced with both increasing demand for digital banking services and higher expectations regarding user experience from consumers (Bowden et al., 2021), as well as efforts by policy makers in the EU to advance digitalization efforts (Savvakis et al., 2024). Consequently, such banks are better able to adapt to and take advantage of a rapidly changing operating environment.

All interactive effects are positive and significant (expect for *network efficiency*). Comparing these results to Table 3, they imply that *digital channel development* and *IT investments* had a more significant impact on profitability post-Covid. This is consistent with recent findings in the DT literature. For example, Savvakis et al. (2024) show that investments in digitalization were more profitable during and after Covid-19 than pre-Covid. Therefore, firms who invested more in DT were better at mitigating the negative effects of the pandemic (Savvakis et al., 2024). However, and in contrast to the above, we find that the *Post-Covid-19* dummy weakens the effect of

[2] We test this potential non-linearity in Section 3.3.

[3] In unreported results we take steps to address how endogenous variables could impact our results; for instance, IT performance could be captured by existing variables. First, we demonstrate that correlations between digitalization index and other factors are low. Second, we present a two-step GMM model, whereby second order lag and difference of the dependent variable are instruments, and remaining explanatory variables are treated as strictly exogenous. Third, we use the Granger causality test between DT index and profitability, which suggests the existence of unidirectional causality. The result demonstrates our findings are robust from endogeneity arising from reverse causality and autocorrelation.

Table 1
Descriptive statistics.

Variables	Mean	std. dev	Min.	Max.	Description	Source
Dependent variable						
ROA	0.57	1.14	−11.43	7.68	Return on average assets	BankFocus
PCA inputs						
Intangibles	0	1	−0.05	26.71	Standardized ratio of intangibles assets (excluding goodwill) to total assets	BankFocus
Employees	0	1	−0.33	19.76	Standardized ratio of total assets to the number of employees	BankFocus and manually collected data
Brances	0	1	−1.11	6.91	Standardized ratio of total assets to the number of branches	BankFocus and manually collected data
Web use	0	1	−0.72	5.72	Standardized ratio of annual web traffic to total assets	BankFocus and Similarweb.com
App use	0	1	−0.36	17.13	Standardized ratio of the number of app's downloads at the end of the year by total assets	Appbrain.com and Andrdoirank.org
App rating	0	1	−1.11	1.39	Standardized yearly average app's rating	Appbrain.com and Andrdoirank.org
Independent variables						
DT index (Factor 1a)	27.08	20.80	0.00	100.00	Index, scaled from 0 to 100	Authors' calculation based on PCA output
Digital channel development (Factor 1b)	26.40	21.33	0.00	100.00	Index, scaled from 0 to 100	Authors' calculation based on PCA output
Network efficiency (factor 2b)	15.75	16.34	0.00	100.00	Index, scaled from 0 to 100	Authors' calculation based on PCA output
IT investments (Factor 2c)	72.51	13.67	0.00	100.00	Index, scaled from 0 to 100	Authors' calculation based on PCA output
Control variables						
Non-performing loans	7.59	9.25	0.00	46.53	Ratio of non-performing loans to gross loans	BankFocus
Total equity	9.98	4.89	3.24	33.40	Ratio of total equity to total assets	BankFocus
Customer Deposits	68.08	17.39	6.45	92.52	Ratio of customer deposits to total assets	BankFocus
Liquid assets	29.02	16.45	3.20	86.75	Ratio of liquid assets to total assets	BankFocus
Gross loans	58.92	19.41	5.05	94.56	Ratio of gross loans to total assets	BankFocus
Cost-to-income ratio	72.24	23.86	31.00	187.03	Ratio of operating expenses to operating income	BankFocus
Income diversification	49.81	14.76	5.98	71.14	Absolute value of each component of total operating revenues (TOR), i.e. net interest income (NII), net fees and commissions (NFC), net trading income (NTI), other income (OTH) and application of the following formula (Elsas et al., 2010): [1 − [(NII/TOR)2 + (NFC/TOR)2 + (NTI/TOR)2 + (OTH/TOR)2]].	BankFocus
Size	15.16	2.20	10.96	20.64	Natural logarithm of total assets	BankFocus
Macro variables						
GDP per capita	10.41	0.52	8.93	11.80	Natural logarithm of real gross domestic product divided by total population	World Bank
GDP growth	1.57	4.22	−11.33	13.59	Annual growth rate of real gross domestic product	World Bank
Concentration	82.76	9.80	44.76	100.00	Sum of each bank's squared market share in a country	World Bank

Notes: The unbalanced panel includes 1516 bank-year observations from 2017 to 2022. Variables are winsorized at 1 and 99 percentiles.

network efficiency. This result could reflect the fact that strategies aimed at reducing the number of branches and employees, which started as early as 2008 (ECB Data Portal), had their largest positive impacts on bank performance much earlier.

In Table 4 Panel B we assess whether the positive impacts of DT vary with levels of country IT adoption. Our *a priori* expectation is that a country's *level of IT* serves as a positive moderator because better IT infrastructure and expertise should allow firms to better leverage their digitalization investments (Karim et al., 2022; Wu and Cheng, 2024) and gain potential competitive business advantages (Dagnino et al., 2021; Wu and Cheng, 2024).

To consider a moderating effect of country levels of IT, in Panel B we utilize the Digital Economy and Society Index (DESI) developed by the EU, which gauges progress toward a digital economy and society in each EU country. We split the sample into countries with high levels of IT adoption (above the 75th percentile of the distribution of the DESI index) and those with lower adoption (below the 75th percentile) and assign banks to a country based on headquarter location.

The findings are mixed. While they suggest a uniform overall effect of the DT index across European countries, they also indicate that the capacity to "spatially capture" customers—relying on a robust digital presence and well-developed digital channels—is more effective in countries with stronger integration of digital technology, superior connectivity, and higher levels of internet user skills and digital proficiency. Moreover, they infer that higher levels of country IT expertise and infrastructure positively influence customer propensity to utilize digital banking services (Wu and Cheng, 2024), and help firms leverage DT investments to gain competitive business advantages (Dagnino et al., 2021; Wu and Cheng, 2024). Thus, the impact of firms' DT efforts are contingent on country level

Table 2
Performance of high IT banks and low IT banks: mean comparisons.

	High-IT	Low-IT	Diff.
ROA	0.890	0.322	−0.568***
Interest income	2.236	1.779	−0.457***
Net fees and commissions	0.784	1.577	0.793***
Other non-interest income	0.145	0.398	0.253***
Staff expenses	1.012	1.864	0.853***
Non-staff expenses	1.170	1.357	0.186*
Cost-to-income ratio	63.260	82.858	19.598***
Customer Deposits	64.140	73.258	9.118***
Gross loans	58.756	56.279	−2.477
Non-performing loans	5.129	9.214	4.085***
Liquid assets	27.945	32.636	4.691***
Total equity	9.856	10.981	1.126***
Size	16.181	13.392	−2.789***

Notes: *Interest income, net fees and commissions, other non-interest income, staff expenses, and non-staff expenses* are divided by total assets and multiplied by 100. High-IT (Low-IT) banks refer to those in the upper (lower) quartile of the empirical distribution of the DT index. Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

Table 3
Baseline regression.

	Dependent variable: ROA				
	(1)	(2)	(3)	(4)	(5)
DT index	0.017**				
Digital channel development		0.009			0.010
Network efficiency			0.026**		0.028**
IT investments				0.035***	0.035***
Non-performing loans	−0.022*	−0.022*	−0.021*	−0.020	−0.020
Total equity	−0.091***	−0.089***	−0.090***	−0.086***	−0.089***
Customer Deposits	−0.008	−0.008	−0.007	−0.008	−0.007
Liquid assets	0.001	0.001	−0.001	−0.001	−0.001
Gross loans	0.008	0.008	0.007	0.007	0.007
Cost-to-income ratio	−0.012**	−0.012**	−0.012**	−0.012**	−0.011**
Income diversification	−0.006*	−0.006*	−0.006*	−0.006*	−0.006*
Size	−0.601**	−0.546*	−0.642**	−0.522*	−0.655**
GDP per capita	−0.678	−0.560	−0.360	−0.331	−0.576
GDP growth	−0.004	−0.005	−0.006	−0.006	−0.005
Concentration	0.022**	0.021**	0.021**	0.020**	0.021**
Number of observations	1516	1516	1516	1516	1516
R-squared	0.100	0.097	0.099	0.105	0.111

Notes: Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

IT infrastructure and expertise (Wu et al., 2021).

3.3. Is there a non-linear relationship between digital transformation and bank performance?

In this section we build on previous studies (e.g., Xiang and Jiang, 2023) to explore potential nonlinearities that may further explain the relationship between DT and bank performance and help clarify conflicting results in the literature (e.g., the profitability paradox). To do so, in Table 5 we include the squared value of the DT measures in the baseline regression (1).

The DT index exhibits a positive linear effect. Interestingly, *network efficiency* and *IT investments* demonstrate opposite non-linear effects. Specifically, the positive marginal effect resulting from banking network optimization diminishes over time. This implies that once an optimal balance between physical and digital branches is reached, further network reductions fail to improve efficiency or profitability.

The results for *IT investments* help explain the profitability paradox (Beccalli, 2007). While our DT measure remains positive and significant, the initial costs of building IT infrastructure results in temporary increases in expenses and reduced operational efficiency. Yet, as digitalization progresses and matures, banks begin to realize gains in efficiency, eventually improving profitability. These findings are consistent with Xiang and Jiang (2023).

4. Conclusions

Extant studies on the impact of digital transformation (DT) on bank performance are typically restricted to single country settings and present mixed findings—partially attributable to difficulties in measuring DT within firms. Departing from prior work we examine

Table 4
Regression with post-covid and high-tech country variable.

	Dependent variable: ROA			
	(1)	(2)	(3)	(4)
Panel A. Covid-19				
Post-Covid Dummy	0.226***	0.240***	0.363***	0.183*
DT index	0.010*			
PCD*DT	0.006*			
Digital channel development		0.008		
PCD*DCD		0.046*		
Network efficiency			0.039**	
PCD*NE			−0.013**	
IT investments				0.025***
PCD*II				0.019**
Number of observations	1516	1516	1516	1516
Bank controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
R-squared	0.106	0.106	0.108	0.111
	Dependent variable: ROA			
	(5)	(6)	(7)	(8)
Panel B. Country IT level				
High-tech country Dummy	0.121	0.094	0.124	0.077
DT index	0.014*			
HTD*DT	0.008			
Digital channel development		0.006		
HTD*DCD		0.011**		
Network efficiency			0.024**	
HTD*NE			0.008	
IT investments				0.032***
HTD*II				0.012**
Number of observations	1516	1516	1516	1516
Bank controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
R-squared	0.130	0.128	0.130	0.136

Notes: PCD = “Post-Covid Dummy”; DT = “DT index”; DCD = “Digital channel development”; NE = “Network efficiency”; II = “IT investments”; HTD = “High-tech country Dummy”. PCD equals 1 for years after 2020, 0 otherwise. HTD equals 1 for countries in the in the top 25 % of the DESI index distribution, 0 otherwise. Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

Table 5
Baseline regression with squared values.

	Dependent variable: ROA			
	(1)	(2)	(3)	(4)
DT	0.019**			
DT^2	−0.000			
Digital channel development		0.010		
Digital channel development^2		−0.000		
Network efficiency			0.053**	
Network efficiency^2			−0.005**	
IT investments				−0.050**
IT investments^2				0.008***
Non-performing loans	−0.022*	−0.021*	−0.021	−0.020
Total equity	−0.090***	−0.089***	−0.090***	−0.087***
Customer Deposits	−0.008	−0.008	−0.006	−0.008
Liquid assets	0.001	0.001	−0.001	−0.001
Gross loans	0.008	0.008	0.007	0.007
Cost-to-income ratio	−0.012**	−0.012**	−0.012**	−0.011**
Income diversification	−0.006*	−0.006*	−0.006*	−0.006
Size	−0.601**	−0.547*	−0.683**	−0.485
GDP per capita	−0.696	−0.569	−0.380	−0.407
GDP growth	−0.004	−0.005	−0.006	−0.006
Concentration	0.022**	0.021**	0.021**	0.020**
Number of observations	1516	1516	1516	1516
R-squared	0.100	0.097	0.101	0.109

Notes: Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

the effect of DT on bank profitability using a novel DT index for a cross-country sample of 279 EU-27 banks from 2017 to 2022. Our main findings demonstrate that higher IT investments and improved network efficiency enhance bank profitability. Furthermore, digital channel development can enhance performance under certain conditions. Notably, Covid-19, along with a country's digital infrastructure and technological expertise, moderate the relationships between DT and profitability, thereby shedding light on their role in shaping the profitability dynamics of banks. Finally, we uncover nonlinearities between DT drivers and performance, which infer that although IT investments initially increase expenses and reduce operational efficiency, they ultimately drive efficiency gains and profitability as DT matures. From a policy and practitioner perspective, our results contributable to understanding as to how investments in DT impact bank performance in the presence of moderating factors. Our findings imply that strategic investments in DT are an increasingly crucial component of firms' competitive strategies (Beccalli, 2007).

Our study is not without limitations, which create opportunities for future research. Notably while we demonstrate that DT investment is generally profitable for banks, it is also apparent that not all types of DT are valuable. Although we consider several dimensions of DT investments, if data becomes available future research could go further into the types of DT investments as well as exploring the boundary conditions under which different DT strategies can help deliver superior firm performance. For example, one avenue would be to exploit passages of country or regional-level policies designed to promote digitization, to better understand which policies are most effective under different institutional contexts.

CRediT authorship contribution statement

Alberto Citterio: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Timothy King:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rossella Locatelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Appendix A

To construct the DT index, we first measure IT investments. One challenge is that disclosures of IT investments are not mandated by accounting standards, banking rules, or stock exchange reporting requirements in the EU. Consequently, there is limited detail, or consistent disclosure, of IT investments within the financial statements of EU banks. However, since literature, patents, trademarks, and capitalized R&D expenses are acknowledged measures for evaluating financial and digital innovation (Gittelman and Kogut, 2003; Lerner, 2002) we can approximate the significance of these elements, and thus the level of investment in innovation, by employing the ratio of intangible assets (excluding goodwill) to total assets. Higher index values indicate greater investment in DT.

Second, following Martín-Oliver and Salas-Fumás (2008) we argue that banks more active in digitalization substitute labor with IT systems, thereby reducing employees in key areas; moreover, that banks with a stronger digital orientation are more likely to reduce overheads and eliminate redundant geographically overlapping branches (Ehrentraud et al., 2020; Boot et al., 2021). Consistent with the previous literature that uses proxies for relationship banking (e.g., Marques and Alves, 2021; van Ewijk and Arnold, 2014), we employ the ratio of total assets to the number of employees, as well as the ratio of total assets to the number of bank branches. In both cases higher ratio values infer more developed digital environments.

Finally, we propose a set of three indices to evaluate the functionality of banks' digital channels and levels of client engagement. First, we evaluate the use of the domestic branch banking websites using data from *Similarweb*, which is recognized for its reliability (Jansen et al., 2022; Prantl and Prantl, 2018; Vaughan and Yang, 2013). Specifically, we measure website popularity as the ratio of annual web traffic to total assets.[4] Additionally, we propose two indices aimed at assessing the popularity of mobile applications (identified by total downloads) and functionality ((approximated by applications' (apps) ratings)). Consistent with prior studies, we retrieve information on Android apps from *Androidrank* and *Appbrain* (e.g., Costa-Montenegro et al., 2012), and restrict our analysis to Android apps due to the absence of historical data on iPhone reviews.[5] Since data are provided monthly, we compute the yearly average rating for each app as a measure of customer feedback on app functionality.[6] To measure mobile app use, we compute the ratio of the number of downloads by total assets—both at the end of the year.

To reduce the dimensionality of the dataset and identify key patterns, we conducted a principal component analysis (PCA) on the

[4] In cases where banking groups maintain multiple websites—whether due to the presence of different institutions or brands within the group, or the existence of separate websites for each country of operation—the total web traffic is computed by aggregating the traffic from each individual site.

[5] Despite this limitation, it should be noted that Android operating systems alone represent 6791 % of the European market (Statcounter, May 2024).

[6] In cases where more than one app per banking group is present, we computed the weighted average using the number of downloads as the weight.

six input variables,[7] the results of which are shown at the top of Table A1. The initial PCA output provided six components, each associated with an eigenvalue and its corresponding percentage of variance explained. These metrics were essential for assessing the importance of each component in explaining the overall variance in the dataset.

To assess the level of DT in European banks, we adopt two parallel strategies based on the output of PCA, as detailed in Panels (a) and (b) of Table A1. In the first approach (a), we create a comprehensive factor, serving as the DT index, by selecting a single component. This approach facilitates the analysis of fundamental relationships between DT and bank performance. To achieve this, we select the component that exhibited the highest eigenvalue and explained the largest percentage of variance. By focusing on this dominant component, we aimed to capture the primary source of variability in the data. We therefore chose Factor 1 (renamed Factor 1a in panel a) as a comprehensive index of DT. The analysis indicates a positive relationship for all variables, suggesting that a higher level of Factor 1a (hereafter referred to as the "DT index") corresponds to a greater digital orientation. The DT index allows us to differentiate between banks with high and low digital propensity and generates a comprehensive indicator that provides an overall measure of digitalization.

In the second approach (b), we adhere to the Guttman–Kaiser criterion (Guttman, 1954; Kaiser, 1960) and select all factors with eigenvalues exceeding 1. This second approach aims to investigate the main drivers of DT in European banks. Use of the Guttman–Kaiser criterion ensures that the extracted factors accurately capture the information within the chosen variables, leading us to retain three factors. For sake of interpretation, the components in Panel b have been rotated using varimax rotation (whereby Factor 1b is derived from Factor 1, Factor 2b from Factor 2 and Factor 3b from Factor 3). The first factor (1b) primarily encompasses variables related to web usage, app usage, and app ratings. Thus, we interpret this factor as a measure of "digital channel development." Factor 2b encapsulates the composition of the labor force and the presence of physical branches, representing "network efficiency." Finally, the third factor (3b) serves as a proxy for "IT investments".

Table A1
Identification of DT indexes using principal component analysis.

Component	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Eigenvalue	1.572	1.536	1.005	0.857	0.605	0.425
Variation explained	0.262	0.518	0.686	0.828	0.929	1.000

a) PCA with 1 component		b) PCA with eigenvalue >1			
Variable	Factor 1a	Variable	Factor 1b	Factor 2b	Factor 3b
Intangibles	0.242	Intangibles	−0.000	0.002	0.982
Employees	0.264	Employees	−0.99	0.678	−0.049
Branches	0.432	Branches	0.084	0.709	−0.049
Web use	0.512	Web use	0.501	0.170	−0.134
App use	0.486	App use	0.629	−0.090	−0.017
App rating	0.495	App rating	0.577	0.007	0.111

Notes: Intangibles is the ratio of intangible excluding goodwill to total assets. *Employees* equates to the ratio of total assets to number of employees. *Branches* is calculated as the ratio of total assets to the number of branches. *Web* use is the ratio of annual web traffic to total assets. *App use* represents the ratio of total number of app download to total assets. *App rating* is obtained as the yearly ranking average of bank's app.

Data availability

The authors do not have permission to share data.

References

Aral, S., Weill, P., 2007. IT assets, organizational capabilities, and firm performance: how resource allocations and organizational differences explain performance variation. Organ. Sci. 18, 763–780. https://doi.org/10.1287/orsc.1070.0306.

Beccalli, E., 2007. Does IT investment improve bank performance? Evidence from Europe. J. Bank. Financ. 31, 2205–2230. https://doi.org/10.1016/j.jbankfin.2006.10.022.

Berg, T., Burg, V., Gombović, A., Puri, M., 2020. On the rise of FinTechs: credit scoring using digital footprints. Rev. Financ. Stud. 33, 2845–2897. https://doi.org/10.1093/rfs/hhz099.

Berger, A.N., 2003. The economic effects of technological progress: evidence from the banking industry. J. Money, Credit Bank. 35, 141–176. https://doi.org/10.1353/mcb.2003.0009.

Boot, A., Hoffmann, P., Laeven, L., Ratnovski, L., 2021. Fintech: what's old, what's new? J. Financ. Stab. 53, 100836. https://doi.org/10.1016/j.jfs.2020.100836.

[7] To understand the correlations among the variables in the input data set we computed a correlation matrix. The correlations, available on request, indicate that correlations amongst variables are at low and moderate levels. These findings further confirm the usefulness of PCA methods in our analysis.

Bowden, J., King, T., Koutmos, D., Loncan, T., Stentella Lopes, F.S., 2021. A taxonomy of FinTech innovation. In: King, T., Stentella Lopes, F.S., Srivastav, A., Williams, J. (Eds.), *Disruptive Technology in Banking and Finance: An International Perspective*. Palgrave Studies in Financial Services Technology. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-030-81835-7_3.

Branzoli, N., Edoardo, Rainone, Supino, Ilaria, 2024. The role of banks' technology adoption in credit markets during the pandemic. J. Financ. Stab., 101230

Ceylan, R.F., Ozkan, B., Mulazimogullari, E., 2020. Historical evidence for economic effects of COVID-19. Eur. J. Health Econ. 21, 817–823. https://doi.org/10.1007/s10198-020-01206-8.

Chae, H.-C., Koh, C.E., Prybutok, V.R., 2014. Information technology capability and firm performance: contradictory findings and their possible causes. MIS Q. 38, 305–326. https://doi.org/10.25300/MISQ/2014/38.1.14.

Chiorazzo, V., D'Apice, V., DeYoung, R., Morelli, P., 2018. Is the traditional banking model a survivor? J. Bank. Financ. 97, 238–256. https://doi.org/10.1016/j.jbankfin.2018.10.008.

Costa-Montenegro, E., Barragáns-Martínez, A.B., Rey-López, M., 2012. Which app? A recommender system of applications in markets: implementation of the service for monitoring users' interaction. Expert Syst. Appl. 39, 9367–9375. https://doi.org/10.1016/j.eswa.2012.02.131.

Dadoukis, A., Fiaschetti, M., Fusi, G., 2021. IT adoption and bank performance during the COVID-19 pandemic. Econ. Lett. 204, 109904. https://doi.org/10.1016/j.econlet.2021.109904.

Dagnino, G.B., Picone, P.M., Ferrigno, G., 2021. Temporary competitive advantage: a state-of-the-art literature review and research directions. Int. J. Manag. Rev 23, 85–115. https://doi.org/10.1111/ijmr.12242.

DeYoung, R., Lang, W.W., Nolle, D.L., 2007. How the Internet affects output and performance at community banks. J. Bank. Financ. 31, 1033–1060. https://doi.org/10.1016/j.jbankfin.2006.10.003.

Ehrentraud, J., Ocampo, D.G., Garzoni, L., Piccolo, M., 2020. Policy Responses to Fintech a Crosscountry Overview. FSI Insights on policy implementation No 23.

Elsas, R., Hackethal, A., Holzhäuser, M., 2010. The anatomy of bank diversification. J. Bank. Financ. 34, 1274–1287. https://doi.org/10.1016/j.jbankfin.2009.11.024.

European Central Bank., 2018. The revised Payment Services Directive (PSD2). Available at: https://www.ecb.europa.eu/press/intro/mip-online/2018/html/1803_revisedpsd.en.html.

Gittelman, M., Kogut, B., 2003. Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. Manag. Sci. 49, 366–382. https://doi.org/10.1287/mnsc.49.4.366.14420.

Guttman, L., 1954. Some necessary conditions for common-factor analysis. Psychometrika 19, 149–161. https://doi.org/10.1007/BF02289162.

Jansen, B.J., Jung, S., Salminen, J., 2022. Measuring user interactions with websites: a comparison of two industry standard analytics approaches using data of 86 websites. PLoS One 17, e0268212. https://doi.org/10.1371/journal.pone.0268212.

Kaiser, H.F., 1960. The application of electronic computers to factor analysis. Educ. Psychol. Meas. 20, 141–151. https://doi.org/10.1177/001316446002000116.

Karim, M.S., Nahar, S., Demirbag, M., 2022. Resource-based perspective on ICT use and firm performance: a meta-analysis investigating the moderating role of cross-country ICT development status. Technol. Forecast. Soc. Change 179, 121626. https://doi.org/10.1016/j.techfore.2022.121626.

Kwan, A., Lin, C., Pursiainen, V., Tai, M., 2023. Stress testing banks' digital capabilities: evidence from the COVID-19 pandemic. J. Financ. Quant. Anal. 1–29. https://doi.org/10.1017/S0022109023000662.

Lerner, J., 2002. 150 years of patent protection. Am. Econ. Rev. 92, 221–225. https://doi.org/10.1257/000282802320189294.

Liu, Z., Li, J., Sun, H., 2024. Climate transition risk and bank risk-taking: the role of digital transformation. Financ. Res. Lett. 61, 105028. https://doi.org/10.1016/j.frl.2024.105028.

Marques, B.P., Alves, C.F., 2021. The profitability and distance to distress of European banks: do business choices matter? Eur. J. Finance 27, 1553–1580. https://doi.org/10.1080/1351847X.2021.1897638.

Martín-Oliver, A., Salas-Fumás, V., 2008. The output and profit contribution of information technology and advertising investments in banks. J. Financ. Intermed. 17, 229–255. https://doi.org/10.1016/j.jfi.2007.10.001.

Pierri, N., Timmer, Y., 2022. The importance of technology in banking during a crisis. J. Monet. Econ. 128, 88–104. https://doi.org/10.1016/j.jmoneco.2022.04.001.

Porfírio, J.A., Felício, J.A., Carrilho, T., 2024. Factors affecting digital transformation in banking. J. Bus. Res. 171, 114393. https://doi.org/10.1016/j.jbusres.2023.114393.

Prantl, D., Prantl, M., 2018. Website traffic measurement and rankings: competitive intelligence tools examination. Int. J. Web Inf. Syst. 14, 423–437. https://doi.org/10.1108/IJWIS-01-2018-0001.

Saka, O., Eichengreen, B., Aksoy, C.G., 2022. Epidemic exposure, financial technology, and the digital divide. J. Money Credit Bank. 54, 1913–1940. https://doi.org/10.1111/jmcb.12945.

Savvakis, G.A., Kenourgios, D., Trakadas, P., 2024. Digitalization as a driver of European SMEs' financial performance during COVID-19. Financ. Res. Lett. 67, 105848. https://doi.org/10.1016/j.frl.2024.105848.

Shang, X., Niu, H., 2023. Does the digital transformation of banks affect green credit? Financ. Res. Lett. 58, 104394. https://doi.org/10.1016/j.frl.2023.104394.

Tang, H., 2019. Peer-to-peer lenders versus banks: substitutes or complements? Rev. Financ. Stud. 32, 1900–1938. https://doi.org/10.1093/rfs/hhy137.

van Ewijk, S.E., Arnold, I.J.M., 2014. How bank business models drive interest margins: evidence from US bank-level data. Eur. J. Finance 20, 850–873. https://doi.org/10.1080/1351847X.2013.833532.

Vaughan, L., Yang, R., 2013. Web traffic and organization performance measures: relationships and data sources examined. J. Informetr. 7, 699–711. https://doi.org/10.1016/j.joi.2013.04.005.

Wu, X., Cheng, G., 2024. The performance and stability of financial institutions after digital transformation: the importance of regional policies. Financ. Res. Lett., 105671 https://doi.org/10.1016/j.frl.2024.105671.

Wu, M., Kozanoglu, D.C., Min, C., Zhang, Y., 2021. Unraveling the capabilities that enable digital transformation: a data-driven methodology and the case of artificial intelligence. Adv. Eng. Inf. 50, 101368. https://doi.org/10.1016/j.aei.2021.101368.

Xiang, X., Jiang, L., 2023. Digitalization and commercial bank performance: a test of heterogeneity from Chinese commercial banks. Financ. Res. Lett. 58, 104303. https://doi.org/10.1016/j.frl.2023.104303.