The complementarities of Digitalization and Productivity: Redefining Boundaries for Financial Sector

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Abstract: Digitalisation is portrayed as a transformative force, remodelling the way we live and businesses operate. In today's unprecedented business environment, the survival of organisations is in technological advancement and online presence. When masses rely on digital financial payments, there is a pressing need for the financial sector to offer innovative products and services to meet customers' needs and achieve sustainable performance. This paper aims to investigate the impact of data analytics on the productivity of banks in Pakistan. Two-step system generalised methods of moments are used for estimation as it addresses endogeneity and reverse causality better than panel regression. The findings suggest that 5.9% productivity is increased for banks that invested in data analytics on average. It was also found that productivity increase is associated with an investment in data analytics compared to a mere investment in any software. However, the moderating role of dynamic capabilities on the relationship between data analytics and banks' productivity is insignificant, which raises a question on the relevance of research and development expense with human capital development. It is recommended that banks should invest in tools and analytics that have predictive, visualising and analytical capabilities. The use of these innovative technologies should be combined with training and human capital development to ensure sustainable firm performance.

Keywords: Digitalization, Data Analytics, Sustainability, Productivity, Banking, Dynamic Capabilities

Introduction

Digital transformation is a new megatrend, leading to data deluge. Globally, the data volume doubles every three years with an average of 2.5 quintillion bytes of data generated daily (Henke *et al*., 2016). Despite knowing the promises of data, most businesses lose more than half the data they possess. Rose (2016) claims that keeping data is now cheaper than deleting it with more advances in information technology (IT), which is why efficient use of big data has become important to corporations' success in today's data-driven environment. Since tools and analytics are needed to extract insight from data, the demand for data analytics (DA) has increased substantially. DA can be defined as 'extensive data usage, statistical and quantitative analysis, and fact-based management to drive decisions and actions' (Davenport & Harris, 2007).

Financial institutions play a prime role in a country's economic development, growth and financial inclusion (Agwu, 2021; Al-Busaidi & Al-Muharrami, 2020). The financial sector helps allocate resources to the intended users through banks and other financial institutes (Cordero, 2019). Since banks work as a bridge, it is not easy to connect with millions of savers and borrowers without information technology. Therefore, the financial sector is amongst the top few potential users of data and information technology across all sectors worldwide (Cordero, 2019). Mobile phones, particularly smartphones, have already been shaped into financial tools for billions of people globally (UNSDG, 2020). Moreover, digital finance has been a vital lifeline for billions in the crisis. Although the current Covid-19 pandemic highlights the immediate benefits of digital finance, the transcendent potential for economic transformation is enormous.

The role of the financial system has become more prevalent in recent years in Pakistan due to its contribution to the country's economic development and GDP growth. The journey of digital transformation has progressed substantially in the current environment due to the unprecedented situation created by the COVID-19 pandemic (SBP, 2020). Notably, access to financial services is critical for achieving a number of the United Nations' sustainable development goals (SDG). These sustainable development goals identify digitalisation and subsequent technologies as enabling tools for sustainable development for countries (Van der Velden, 2018). In accordance with SDG, the United Nations (UN) recommends less developed countries build affordable digital infrastructure, improve digital skills, and make digital financial services accessible to everyone (UNSDG, 2020). Moreover, innovations and IT investment have underpinned a rapid scaling of assistance to underprivileged communities, from widening the scope of social safety networks and health services to innovative ways of securing digital livelihoods and supporting each other in communities and societies (UNSDG, 2020).

At present, the banking sector of Pakistan is the true recipient of data analytics as there is an enormous volume of data resulting from digital transactions (SBP, 2020). While the dimension of bank's digitalisation includes online banking, digital channel and digital online intensity (Carbo-Valverde *et al*., 2020), this study digs deeper to identify banks' digital transformation with more than just going digital but investing in analytics. This includes using software with analytical and predictive capabilities and dashboards for decision making.

Nevertheless, the empirical evidence on the nexus between data analytics and firm performance in the financial sector is scant. Moreover, the current literature can be distributed on two extremes: one focuses largely on the developed countries such as UK, USA, Italy, and Australia and the other focuses on the emerging economies including Turkey, Malasia, and India. The former focuses on investigating the business value of advanced technologies such as big data analytics (BDA), algorithms and machine learning (Brynjolfsson & McElheran, 2019; Muller *et al*., 2018) whereas the latter focuses on the performance outcome of very basic digitalisation tools such as internet banking, Automated Teller Machines (ATMs), and social media presence (Coulibaly, 2020; Carbo-Valverde, 2020; Romdhane, 2013). However, the investment in data analytics is largely unexplored, which falls between these two IT extremes and many banks in Pakistan have invested in these analytics as BDA investment is still exceptional in the country.

While financial players include banks, insurance companies, capital investment companies, the banking sector dominates Pakistan's financial system (SBP, 2015). Therefore, this study focuses on the banking sector of Pakistan including commercial banks and microfinance banks. The specific objective of this study is as follows: *to investigate the impact of data analytics on the productivity of banks in Pakistan while controlling firm-specific factors and macroeconomic variables.* The findings of this study will be equally important to both scholars and policy makers as these will validate the assumptions and hype around big data, data analytics and banks' productivity. Although firms across the globe have recognised the significance of data analytics and are ready to invest in them, the investment in innovative technologies is not as simple as it seems. It requires much more than a customary investment in data analytics, such as developing training programs and building dynamic capabilities (DC) (Shan *et al*., 2019). Hence, the moderating role of DC will also be explored to see how DC will moderate the relationship between DA and productivity.

IT and Productivity of the Banking Sector

Various studies have been conducted to investigate the relationship between IT and productivity (Brynjolfsson &McElheran, 2019; Shan *et al.,* 2019; Muller *et al*., 2018; Tambe *et al*., 2012). Among the various techniques to measure the impact of IT on firms' productivity, the most commonly used model is the Cobb-Douglas production framework, which offers multifactor productivity. Cobb and Douglas introduced this framework in 1928 to model the growth of the US economy from 1899 to 1922. The theoretical form of the model is given in equation 1:

$Y_{it} = bL^{\alpha}K^{\beta}$ ------------------- *(equation 1)*

where b is the total factor productivity, α and β the output elasticities of labour and capital. As shown in equation 1, the Cobb-Douglas framework offers a simplified view of an economy or a firm where the production output is associated with the amount of labour and capital invested. However, this simpler model has been extended with other production inputs such as IT and energy following (Brynjolfsson *et al*., 2019; Muller *et al*., 2018; Octrina & Setiawati, 2019). Since this model proved to be remarkably accurate at firm-level studies, the current study also utilises this production function in its extended form to identify the impact of investment in data analytics on the banking sector's productivity in Pakistan.

However, there has always been a debate on 'correct' definitions of input and output measures in the banking sector. Currently, there are five commonly used approaches for defining bank outputs and inputs in the literature, a brief detail of which is given in Table 1.

Business Value of IT in Banking Sector

The increased use of digital financial services and technology for business and social interactions across the world has put pressure on banks to invest in modern banking technologies aimed at efficient and improved services for their customers (Carbó-Valverde *et al*., 2020). Niemand *et al*. (2020) find that technology is changing business models of various industries including banking sectors in Liechtenstein, Germany and Switzerland. Therefore, banks need to modify their business models according to digitalised innovation to remain competitive. Digitalisation has largely altered the way banks interact with their customers, from face-to-face to digital financial services. However, digitalisation does not mainly affect the profitability of the banks, but also helps develop innovative ways of doing business and taking risks (Niemand *et al*., 2020).

Puschmann (2017) finds that Fintech-based business models outperform traditional banking systems. However, commercial banks' productivity may improve if IT is incorporated into their business functioning and decision making (Surulivel *et al*., 2013). Various studies confirm the business value of IT in the banking sector in different countries, including the US (Muller *et al*., 2018), Germany (Koetter & Noth, 2013), Spain (Martín-Oliver & Salas-Fumás, 2008), Nigeria

(Ogunyomi & Obi, 2016) and Pakistan (Gul et al., 2021; Gul & Ellahi, 2021). These studies show that digital solutions such as eBanking, branchless banking, and online banking improve the competitiveness of banks and offer customers discontinued services that reduce the total costs and increase productivity.

Hypothesis Development

Resource Based View: Apparently, IT investment can enhance the efficiency and competitive advantage of companies as an asset or a resource (Brynjofsson *et al*., 2019; Koetter & Noth, 2013). The resource-based view (RBV) sees an organisation as a hub of resources (Barney, 1991, 2007) and can enhance firms' performance if these resources are unique and valuable. Many scholars have developed its relevance in explaining the relationship between IT investment and performance (Lioukas *et al.,* 2016). Maroufkhani *et al.* (2019) find that RBV is the most used theory to explain the link between big data analytics and firm performance. Since data analytics is close to BDA, this study uses RBV to explore the impact of DA on banks' productivity. Theoretical backing and associated empirical literature posit that being data analytics (DA) rare and imitable resource, investment in DA should enhance banks' productivity. Embedded on the resource based view and the empirical evidence, the current study develops its first hypothesis as follows:

H1: Investment in data analytics has a positive impact on the productivity of banks in Pakistan.

Dynamic Capability View: Extending RBV, Dynamic Capability View (DCV) aims to explain how organisations can constantly acquire valuable, inimitable and competitive resources to compete a marketplace. Teece (2007) introduced DCV and defined dynamic capabilities as *"the ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments"* (p.517). New technologies are continually developing and breeding new competition in today's data-driven and information-centred global markets. Dynamic Capabilities enable companies to become adaptable, dynamic and responsive to new opportunities and threats (Teece, 2007). RBV argues that a competitive firm possesses inimitable and unique resources (Grant, 2002), whereas DCV argues that an organisation will perform better in terms of financial performance if it has the desired set of capabilities to manage its critical resources. Thus, the firm performance is further enhanced with dynamic capabilities that change the ordinary capabilities into dynamic while widening a firm's resource base (Rehman *et al*., 2020; Laaksonen & Peltoniemi, 2018). These arguments serve as the basis of the second hypothesis of this study which is as under:

H2: The dynamic capability of banks moderates the impact of investment in data analytics on productivity.

Materials and Methods

Data and Sources of Data

Data was collected for a sample of commercial and microfinance banks operating in Pakistan from 2010 to 2019. This was the most suitable sample period as digitalisation of Pakistan's banking sector took place in 2008-2009 (Asher, 2021) and the effect of digitalisation takes at least a year to show in performance measures. Overall, 33 commercials banks and 11 microfinance banks were registered with the State Bank of Pakistan (SBP) in 2019. However, the study excluded foreign banks from the sample due to their small operation size in Pakistan. Additionally, we excluded four specialised banks from the sample due to the different nature of operations and target market, the final sample consists of 36 banks including 10 microfinance banks and 26 commercial banks. The data was collected from the handbook of statistics on the Pakistan Stock Exchange, State Banks of Pakistan, and respective banks' annual reports. The annual frequency data was collected for ten years with a total of 330 firm-level observations.

Construction of Variables

The present study utilises multiple variables to conduct the econometric analysis. The main variable of interest is data analytics. The empirical literature on constructing DA as a proxy of IT investment for secondary data is scarce. Tambe (2014) used Hadoop investment for big data technologies and measured it through the number of technical workers who had Hadoop skills. Muller *et al*. (2018) measured BDA assets as binary assets: record 1 when the firms go live with BDA assets and the following years, and 0 otherwise. The current study also used the same methodology and measured DA as a dummy variable: records 1 in the year and the following years when a firm goes live with data analytics and zero otherwise.

Insert table 1 here.

Methodology

Generalised Method of Moments (GMM). The dependent variable of all the models used in this study is the performance variable which is affected by its previous values (Ehsan & Javid, 2018). This feature makes the panel estimation dynamic process. Ignoring this aspect and not including the past value of the dependent variable as an independent variable would produce a misspecified equation. Researchers like Baum and Baum (2006), Roodman (2009), Baltagi (2008) highlighted the applicability of dynamic panel models where T (time) < X (cross-section). Therefore, in the present study GMM estimation technique was appropriate as for 36 banks over 10 years as time is less than cross-sections. Roodman (2009) stated that in financial data, due to the shortage of appropriate instruments from outside, valid instruments could be generated from within the existing data by taking lag values or differenced values of a variable. Concluding the merits and demerits of possible estimation methods, it was decided to apply a two-step system GMM to investigate the impact of DA on banks' productivity.

Estimable Models

Model 1 Impact of DA on Productivity of the banks. The Cobb-Douglas production function is typically estimated in firm-level panel data. The residuals of this equation can be interpreted as firm productivity after accounting for the contributions of all inputs. Including additional firm factors additively into this equation can be interpreted as the marginal effect of the factor on firm productivity (Muller *et al*., 2018; Koetter & Noth, 2013). The first estimable equation is as follows:

$$\boldsymbol{log(Y_{it}) = \beta_0 + \beta_1 DA_{it} + \beta_2 log(K) + \beta_3 log(L) + \sum_{i=0}^{t} \beta_i X_{it} + U_{it}} \quad \text{..... (equation 1.1)}$$

Where Y_{it} is the output of the extended Cobb-Douglas production function, Y_{it} was measured through five output variables, namely i) Total Assets (Y1), ii) Working Assets (Y2), iii) Sum of Deposits and non-bank Loans (Y3), iv) Non-Bank Loans (Y4) and v) Earning Assets (Y5). DA_{it} is a dummy variable: 1 for banks that have adopted DA and the following years and 0 otherwise. K_{it} is the capital measured through fixed assets. L_{it} is the number of full-time employees. $\sum \beta_i X_{it}$ represents the matrix of control variables which include deposits to asset ratio (Deposits), non-performing loans to total loans (NPL), Z-score (Z-Score), Capital adequacy ratio (CAR), type (Type), listing (Listing), GDP growth (GDP_g), and Inflation (INF). U_{it} is a random error term.

Model 2 Role of Dynamic Capabilities for Productivity of Banks. The following model was employed to identify the moderating impact of dynamic capabilities on the relationship between DA and banks' productivity. The R&D expense measured through training expense was used as a proxy for dynamic capability (Hsu & Wang, 2012). All the variables are as explained in Table 1.

$$\boldsymbol{log(Y_{it}) = \beta_0 + \beta_1 DA_{it} + \beta_2 (DA * DC) + \beta_3 log(K) + \beta_4 log(L) + \sum_{i=0}^{t} \beta_i X_{it} + U_{it}} \quad .....$$
(equation 1.2)

The interaction term of DA and DA measure the moderating impact of DC on the relationship between DA and productivity. All other variables employed in equation 1.2 are the same as in model 1.

Analysis of Results

Descriptive Statistics

According to the descriptive statistics presented in Table 2, the study shows that on average, log output under each output method is eight. It shows that, on average, there is not much difference in the output measures used in the study which is consistent with Koetter and Noth (2013). Productivity input variables are measured through the log of employees (L), log of capital (K) and Data analytics (DA). Very few banks spend on training, particularly in the early years of the study period (2010 to 2014), that is why training expense has only 228 observations.

Insert table 2 here.

Correlation Matrix:

The correlation matrix of all the variables used in the study is presented below in Table 3. Five output variables are significantly correlated with each other. The correlation matrix shows no high correlation among independent variables including labour, capital and DA. Our main variable of interest has a negative correlation with non-performing loans, inflation and capital ratio. The results are consistent theoretically as data analytics investments should reduce the non-performing loans and equity investment. Growth in GDP and age of the bank has a positive correlation with DA investment.

Insert table 3 here.

Impact of DA on Productivity of Banks

We test the model (equation 1.1) using GMM system estimation with lagged dependent variable and introducing instruments in the model. The primary results regarding the estimates of DA and other productivity inputs on five types of banks' output are presented below in Table 4. As the Cobb-Douglas production function given in equation 1.1 is in log transformed, the DA dummy variable's coefficient can be interpreted as the percent productivity change associated with owning DA assets (Muller *et al*., 2018).

Column 1 of Table 4 shows the productivity estimates of DA on Y_1 (total assets), showing positive and significant results. The findings suggest that an increase of 1% in DA investment causes the productivity in terms of total assets to increase by 1.82%. Column 2 of Table 4 shows the productivity estimates of DA on Y2 (working assets), the results show positive and insignificant results. The findings suggest that an increase of 1% in DA investment causes the productivity in terms of working assets to increase by 1.02%. Column 3 of Table 4 shows the results of the impact of DA on Y3 (deposits and non-bank loans) and the results are statistically significant at 10%. The findings suggest that live DA assets are associated with 12.47% productivity of banks. Column 4 of Table 4 shows the results of impact of DA on Y3 (non-bank loans) and the results are statistically significant at 10%. The findings suggest that live DA assets are associated with 13.39% productivity of banks. Column 5 of Table 4 shows the results of impact of DA on Y5 (earning assets) and the results are statistically significant at 10%. The findings suggest that live DA assets are associated with 7.07% productivity of banks.

The coefficients of capital are positive but insignificant across all output models and the results are consistent with Koetter and Noth (2013). The inefficiency or negative contribution of capital in the presence of IT (DA in our case) is implausible. The impact of coefficients of the number of employees (L) on all the output measures is positive and significant at 1% (except for column 5 of Table 4, where the coefficient is significant at 10%). Across all columns, non-performing loans, zscore, LIST and GDP_g are insignificant.

Various diagnostic measures are also reported in Table 4 including the Hansen test for overidentifying the model and instruments and Arnallo-Bond for autocorrelation. Hansen test does not reject the null hypothesis of over-identification of the model and instruments used in GMM and IV. The second-order autocorrelation is rejected across all the output models. The study's overall findings are consistent both with general literature (Brynjolfsson *et al*., 2019, 2011; Muller *et al*., 2018) and bank-specific literature (Coulibaly, 2020; Akkaya, 2017; Koetter & Noth. 2013). Thus, we fail to reject the first hypothesis (*H1*) and conclude that the investment in DA is associated with an increase in productivity of 5.96 (on average) is higher for those banks that invested in DA. The coefficient estimates are in line with Muller *et al*. (2018) but conservative compared to the estimates by Koetter and Noth (2013).

Insert table 4 here.

Role of Dynamic Capabilities

An extension of Table 4 is given below in Table 5: it presents the GMM estimation of the model given in equation 1.2. This model investigates the impact of dynamic capabilities (DC) on the relationship between DA and productivity outputs. DC is measured through training expense as a proxy for R&D. The interaction term of log training expense with DA is used in the model.

The impact of DA is positive and significant on all the output models except for output Y2. The DC*DA interaction term introduced in the model does not significantly impact the bank output. However, this term's inclusion into the model enhances the coefficients of DA by 1% to 2%. This shows that though DC does not directly affect the output, it strengthens the impact of DA on the productivity of banks. Across all the models, the coefficients of capital remain positive and insignificant consistent with (Koetter & Noth, 2013). The coefficients of labour has positive and significant at 1% across all the output models (except for column 5 of Table 5, where the coefficient is insignificant). The type of the bank is significant in the rest of the output models except for column 5 of Table 5. The findings suggest that output differs across the type of banks.

Various diagnostic measures are also reported in Table 5 which confirm that our results are unbiased and robust. To the best of our knowledge, no empirical study has ever investigated the tested the impact of DC measured through financial variables on the relationship on DA (or BDA) and productivity through econometric models. The results are inconsistent with the findings of the survey-based studies that used dynamic capabilities as a moderating variable to investigate its impact on the relationship between BDA and firm performance (Abbady *et al.,* 2019; Mikalef & Krogstie, 2018; Vitari & Raguseo, 2018). Inconsistent results with the previous studies should be taken with care as the survey-based studies suffer from response bias (Suchman, 1962). Yet, the insignificant results suggest that either the dynamic capabilities measured through training expense fail to fully reflect R&D expense or training is not effective in developing human capital in the best utilisation of data analytics. Thus, we reject the null hypothesis (*H2*) and conclude that dynamic capabilities do not moderate the relationship between DA and productivity.

Insert table 5 here.

Discussion

We used a two-step system GMM to identify the impact of DA on the productivity of banks. Pertaining to the banking sector, five types of output measures are included in the analysis; Y1 (total assets), Y2(working assets), Y3(deposits and loans), Y4(loans), and Y5(earning assets). Except for Y2 (working assets), the impact of DA on all four output measures is significant, consistent with previous literature (Muller *et al*., 2018; Koetter & Noth, 2013). The first hypothesis is fully accepted and we conclude that DA investment causes productivity to increase by 5.96% for the banks in Pakistan. Moreover, the findings suggest that information technology is an intermediate input for productivity studies in the banking sector (Koetter & Noth, 2013). Therefore, investment in IT should be included in the productivity studies particularly focused on banking sector.

The above literature review highlights that digital data itself may not create value for organisations and they must have internal practices and methods suitable to put resources into value creation (Wilden & Gudergan, 2015). Additionally, dynamic capabilities change a firm's broader resource base into sustainable firm performance if organizations are able to transform fully (Laaksonen & Peltoniemi, 2018). Therefore, we also introduced dynamic capabilities (DC) of an organization into our model as a moderating variable to identify if it can modify the relationship between DA and banks' productivity. The role of dynamic capabilities was measured through training expense as a proxy for R&D expense. We argue that training of employees is a good proxy in the absence of R&D expense for multiple reasons. The investment in novel technologies needs innovative training programs and human development. If employees are not well-trained to use technology in decision making, the incumbents would not be able to gain a sustainable competitive advantage.

Our findings suggest that DC has a positive but insignificant impact on the relationship between DA and Banks' productivity. Therefore, it seems that dynamic capabilities do not moderate the relationship between DA and productivity, raising a question on the quality of training programs of the banking sector and their relevance to DA. Human development and training has remain a considerable

Conclusion

Despite the fastest growing IT markets and hype built around investment in data analytics to reap the associated benefits, the empirical evidence is scarce, particularly in the emerging economic context. This paper is one of the first papers to investigate the impact of data analytics on banks' productivity in Pakistan. The findings suggest that, on average, 5.9% productivity is increased for the banks that invested in DA. Since GMM addresses the endogeneity and reverse causality better than panel regression and was also recommended by previous studies (Muller *et al*., 2018; Koetter & Noth, 2013), this study uses two-step system GMM estimation. As the moderating role of dynamic capabilities on the relationship between DA and banks' productivity is insignificant, it raises a question on the quality of training programs and human capital development in the banking sector.

This study sheds light on our response to the current unprecedented crisis and national goal to meet SDG through leveraging digitalisation. We explored the most prominent sector i.e. banking sector of the country in terms of its contribution to GDP growth, economic development, helping vulnerable citizens, reducing inequality, and increasing financial inclusion (SBP, 2020). In contrast, if unchecked and unmonitored for the digital recital, the poor performance of the banking sector may lead to the catastrophe of countries due to the trickle-down effect against the UN's agenda of SDG. Therefore, we recommend Pakistani banks to invest in data analytics and digitalisation at their earliest not only to achieve a sustainable performance but also to align with the national goals of digital Pakistan and SDG.

Theoretical contribution: This study makes several theoretical contributions to the existing literature on data analytics, digitalisation and Banks' productivity.

First, the results of this study contribute to answering a profound question in data analytics research. The prominent studies that investigated the impact of big data analytics on organisational performance in the context of Pakistan are survey-based (Ali *et al*., 2020; Shahbaz *et al*., 2020; Shabbir & Gardezi, 2020). Since no sector in Pakistan is fully utilising BDA, which depicts that the survey respondents of these studies might not have the actual experience or exposure of big data, and that the responses and capabilities that they entail are entirely perceptual. We argue that the confirmation of enhanced organisational performance based on survey-centered fail to reflect the actual outcome of BDA investment. Conversely, our study investigates the actual outcome of data analytics based on published financial reports.

Second, it is one of the very first researches that assess the impact of data analytics on productivity of banks with the moderating role of dynamic capabilities measured through financial variables. Despite the fact that there is a lot of research on IT investment in the banking sector (for example Coulibaly, 2020; Akkaya, 2017; Koetter & Noth. 2013), there is nascent research on combining dynamic capabilities with IT in econometric studies.

Third, this research contributes to the body of knowledge about banks' productivity. In literature, the output of banks has remained a contentious subject. The "correct" measure of bank performance is still a source of an ongoing debate in banking literature (Martin-Oliver & Salas-Fumas, 2008). We used five different output proxies to account for this uncertainty. The findings are consistent across a variety of bank output measures, indicating that the choice of output parameters has little bearing on the study's key conclusion that data analytics has a positive and significant impact on banks' productivity.

Finally, the current study's main strength is its use of a lagged research design through employing system GMM estimation which entails that the enhanced productivity is due to DA investment and is not subject to causal or endogeneity issues.

Managerial Contribution: This study has profound implications for the firms and professionals including bank managers, policymakers, incumbents and consultants. *First*, this study offers an insight into the actual outcome of the investment in DA which is highly relevant to the policymakers and regulators to understand its significance and develop policies to facilitate its smooth adoption. *Second*, by offering the magnitude of productivity estimates, this study will facilitate the decision makers and incumbents to conduct the cost-benefit analysis before investing in data analytics. The incumbents would know exactly how much productivity would be increased if investment in DA is made. *Thirdly*, this study identifies that dynamic capabilities measured through training expense are not effective and up-to-the-mark. The executives and managers should invest in dynamic and relevant training programs to develop human capital. *Finally,* this study clarifies that current pandemic-induced lockdowns are pushing businesses to be online therefore, the firms need to be at the forefront of digitalisation to make their presence sustainable and competitive in the long run.

Limitations and Future Direction: This study has few limitations too. The study only focused on the banking sector, therefore the generalizability to other sectors remains limited. Other plays of the financial system such as Fintech and insurance companies should also be explored to offer a wider picture of digitalisation of the financial sector. In future, other aspects such as risk measures, financial stability and employee productivity should also be studied to document a more rigorous view on the performance outcome of BDA. We measure the dynamic capability through training expense which largely reflects on human capital development. In future, DC should also be measured through alternative proxies such as advertising expense, patents, and intangible to cater to the larger view of dynamic capabilities.

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