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The impact of digitalization on credit risk: the mediating role of financial inclusion (National Bank of Egypt (NBE) case study)

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ABSTRACT

This article investigates potential direct and indirect impact of National Bank of Egypt (NBE) digitalization and its financial inclusion on credit risk. The methodology used in the study is an empirical technique through the collection of secondary data from the period between 2011 and 2021 in the Egyptian banking sector. To accomplish this, the study developed two hypotheses employing the empirical SEM model for testing whether there is a positive or negative impact for three chosen variables: digitalization, credit risk and financial inclusion. The investigational outcome shows that NBE digitalization has both direct and indirect impact through the mediator variable, financial inclusion. It also provides an understanding of the relationship between digitalization, credit and financial inclusion. The article proposes for future studies the impact of other Fintech factors directly and indirectly using the mediators on credit risk. The authors came up with many findings: first, financial inclusion indices can be built using portable money and banking services activities. Second, digitalization has a negative direct impact on credit risk. Also, digitalization has a positive indirect impact on credit risk through the mediator variable which is referred to as financial inclusion. Third, the model fit is adequate for the data being tested.

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Digitalization; credit risk; financial inclusion; Egyptian banking sector

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1. Introduction

The Egyptian banking industry encountered many serious challenges in the recent years.

In an overview of the Egyptian banking sector, Kalhoefer and Salem (2008) noted that Egypt's development performance changed from a deterioration stage in the mid of 1980s further to the decline of the oil prices, to recovering in 1990s, then a second

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failure happened during the period between 1999–2003. Hence, we can say Egypt passed across several stages.

However, when the Egyptian government began privatization in the entire segments, the economy developed. During the COVID-19, the Egyptian banking sector was impacted. Hence, according to Fitch (2021), Egyptian banks suffered from a deterioration on their asset quality and stress remained on their profitability through 2021 during the economic domino effect of the pandemic. On the same line, the concern remains for the current year 2022; whereas, Fitch (2022) in a recent report noted that the depreciation was primarily motivated by deteriorating of the foreign assets and if the tendency will remain, the banks' foreign-currency (FC) liquidity and debt service ability might be controlled. Since digitalization contributes to better banking operations, the importance of employing digitalization in the banking sector is the focus on many banking regulators. In that regard, KPMG (2020) explained that 'banking is at a revolutionary crossroads'. Digitization methods to protect the cost-base and to enhance the regulatory and supervisory practices and related data in internal structures are progressively turning into a planned resolution.

Generally speaking, digital transformation gives Egypt an exceptional chance to change numerous economic areas, mainly the financial sector at the same time generating economic growth for both individuals and institutions. In this paper, the authors open the loop on the impact of the digitalization and its financial inclusion on the credit risk. As evidence from the Egyptian's banking sector, Salman (2021) noted that Egyptian banking industry endures from the low rates of financial inclusion due to the great involvement of the informal industry in business events. To encourage financial inclusion in Egypt, the proposal of the Central Bank of Egypt (CBE) was to strengthen the provision of financial technology facilities since many technological services are offered in the Egyptian banking sector. In an example of the importance of the financial inclusion, Alexbank (2017) in their report noted that Egypt has put financial inclusion as a main concern throughout the last years. The Central Bank of Egypt (CBE) contributed in various local and international projects to enhance financial inclusion in Egypt. In July 2017, Egypt was selected, alongside with China and Mexico, as a standard nation in a recent Financial Inclusion Global Initiative initiated by the World Bank Group. The importance of this study lies behind the huge prospects that have been associated to technological advancements that transformed the business world to offer more income and expectations. The paper employs two technical techniques to test the proposed hypotheses and derive the relevant outcomes.

From the contribution perspective, the results of the research are of interest to practitioners in the field, banking regulators and banking executives and to academics, to the financial scholars. The main contribution of the paper lies behind the emerging topic of financial digitalization mainly in the current period of fast innovation advancement that is being introduced worldwide in all the disciplines. Similarly to the importance of financial digitalization, financial inclusion eases daily living, and supports households and industries plan for anything from long-run objectives to unpredicted crises.

More specifically, since the research focuses on the Egyptian banking sector, the results are to be employed within the Egyptian's banking sector and maybe the case could be inspiration to the financial regulators in other banking sector in the region or outside.

The paper is structured with four sections. Section 1 introduces the related work, followed by Sec. 2 where a comprehensive review of literature is made. Section 3 introduces the proposed methodology. Section 4 is devoted to the discussion on the findings and lastly Sec. 5 concludes

2. Literature review

2.1. Digitalization and credit risk

Shcherbatykh et al. (2021) explained that in the Ukraine's banking sector, before the health pandemic of COVID-10, digital growth was considered unique and advanced since it was likely to rise the volumes together in traditional and standard ways, through growing the branch network; however, in 2020 it became sufficient to aggressively progress without digitizing its procedures hard. For the relationship between digital transformation and credit risk on the banking sector, Bahillo et al. (2016) clarified that digital transformation in credit risk management gives more transparency to risk reports. Having stronger control on risk, banks can develop their operations, throughout further focus on risk centered pricing, quicker customer assistance without damaging the risk concentrations, and additional efficient supervision for current portfolios. An example of banking innovation of Bitcoin, A study by Zhang et al. (2021) found out that that Bitcoin should be examined cautiously to maintain financial stability as there is risk consequences for applicants in both the Bitcoin and conventional economic markets. At the contrary, some scholars view that banking digitalization can have a negative impact on the banking operations and hence affecting credit risk. For instance, Starodubtseva et al. (2021) points out that digitalization has negative consequences, particularly these days, such as greater bank's costs for the launching of technologies, training employees, information security, the issue of labor force, that might adversely impact the workplace in the country. Westall (2022) in a recent report announced the downgrade for the first time in nearly a decade following Moody's Investors Service reduced its outlook to negative. In that perspective, Moody's explained that the outlook modification from stable to negative shows the increasing disadvantage risks to the sovereign's outside shock absorption capability in light of an important reduction in the foreign exchange reserve cushion to confront future outside debt facility payments. Furthermore, Luz (2019) concluded that due to the digital alteration of current procedures, productivity improves in managing times. Adding, shaping the credit risk style enhances bank assessment while improving clarity, reliability and management in the commercial lending procedure.

Digitalization and financial inclusion

The World Bank (2015) described digital financial inclusion as the process that includes the placement of the cost-saving digital resources to spread presently financially excepted and underserved people through a variety of official financial facilities suitable to their requests that are reliably distributed at a reasonable cost for clients and maintainable to providers.

Nowadays, it became obvious that financial inclusion has to be a fundamental objective of the worldwide economic system. On that idea, IFAC (2021) is anticipating that by 2030, more than 95 percent of the globe's people will have gain access to the Internet all through a smart mobile phone. Therefore, governments worldwide must now focus on the Digital inclusion realizing that financial inclusion, commerce, and growth are directly associated to the development of the smart mobile phone and the internet. Hence, the advantages of financial inclusion are several. Gamil (2021) clarified that acknowledging the significance of the digital transformation to support the financial inclusion in villages' societies; Egypt has created a cashless economy where it has presented technology-centered guidelines yet prior to the COVID-19 epidemic. He added also that the financial inclusion ratio in several emerging nations like Kenya, China, and India, remains over 80%. Once contrasted to these states, Egypt holds a minimal financial inclusion ratio and a tiny number of people employed in the official segment that will impact stakeholders' assessment of Egypt's development. Additionally, some scholars highlighted on the importance of the digital financial inclusion as a tool used for financial resiliency to react to crisis for the example, the latest health crisis of COVID-19. For instance, Ayadi and Shaban (2020) discussed that further financially inclusive nations are well prepared to reach out to minimal revenue and weak groups that have a tendency to be harshly affected by the epidemic. To cope to this worldwide disaster, administrations, financial organizations and FinTech corporations working in South-East Mediterranean and Africa will have to establish their attempts to offer advanced explanations and to rapidly reply to the larger demand for financial inclusion, through digital resolutions and platforms and additional organizational digital financial learning plans.

Financial inclusion and credit risk

Banking stability might be affected from financial inclusion. In that regard, Ghasarma et al. (2019) found out that governments and banks should have perceptions to expect credit risk which can impact the banking steadiness due to financial inclusion. On the other side, the financial stability is affected by digital finance and its consequence for financial inclusion. Ozili (2018) and Metawa and Mirza (2022) noted that digital finance has positive impacts for financial inclusion in developing and progressive markets, and the benefit that digital finance offers to people with small and inconstant revenue is frequently further valued to them than the higher cost they will pay to acquire these facilities from traditional controlled banks. In spite of the advantages of digital finance, the author emphasized certain thread that digital finance present for financial inclusion and financial steadiness. Research paper demonstrating the relationship among financial inclusion and credit whether positive or negative and their effect on financial stability still limited. In that regard, Khan (2011) has cited that financial inclusion can offer negatively to financial stability. One of the primary objectives of the financial inclusion is to permit people and companies to obtain loans. On the same line, Farid (2020) concluded that the nations the most impacted by credit risk due to the financial inclusion programs are Algeria, Egypt, Iraq, Jordan, Kuwait, Libya, Morocco, Syria, Tunisia, UAE and Yemen. The author also concluded that financial inclusion has a positive influence on the stability of the banking system however on the long time.

Sample

The population which is used in this study consists of all Egyptian Commercial Banks. National Bank of Egypt (NBE)'s data is used as a case study for testing the two main hypotheses of this study during the period from 2011 till 2021. The time-series is built using yearly data which is collected from NBE electronic site, reports, and financial statements. NBE is the oldest bank within Egyptian commercial banks. It was established on the date of June 25, 1898 with a capital of £1 million. During its long history, NBE's functions and roles have continually developed to adapt with the different Egyptian economic and political stages. During the 1950s, NBE assumed the Egyptian central bank's duties. After its nationalization within the 1960s, it acted as a pure commercial bank side by side with carrying out the functions of the central bank in the Egyptian lands, where the latter had not any other branches. Moreover, since mid-1960s, NBE has been in charge of issuing and managing investment certificates on behalf of the Egyptian government. During Financial years 2019/2020, NBE managed to achieve unprecedented performance indicators. Total financial position as at the end of June 2020 recorded EGP 2 trillion, growing 23% Year-Over-Year (YOY). Accordingly, NBE's total assets accounted for 31.5% of Egyptian banks' total assets. NBE's financial position continued to scale up to EGP 2.5 trillion by the end of March 2021 (NBE, 2022).

There are three variables in this study. Digitalization is used as an independent variable. Additional, credit risk is used as a dependent variable. Finally, financial inclusion is used as a mediator variable. For digitalization variable, it is measured by an index built using first principal component analysis of portable money index and electronic debt and credit card index (Aboel-Ezz, 2021). Portable money index is measured by dividing the value of financial transactions made using portable money during the year by Gross Domestic Product (GDP). Electronic debt and credit card index consists of two variables. The first one is the natural log of number of loans per 100,000 adults. The second one the natural log of number of credit cards per 100,000 adults. For credit risk variable, it is measured by an index which is resulted from dividing bad loans by total loans (El-Madarma, 2021). For financial inclusion variable, it is measured by an index built using first principal component analysis of four variables. These variables are banking services availability, access, usage, and financial inclusion indicator (Aboel-Ezz, 2021 and El-Madarma, 2021). Banking services availability is built using two variables which are number of branches and that of Automatic Transfer Machines (ATMs). Banking services access is measured by number of credit cards issued till this year. Banking services usage is measured by dividing number of debts and loans by Gross Domestic Product (GDP). Financial inclusion indicator is resulted from dividing accrual loans in small and medium enterprises (SMEs) by total loans. Finally, we use two control variables for financial inclusion index used in our study, namely inflation rate and population growth rate (Aboel-Ezz, 2021).

3. Methodology

This study is implemented in an empirical format using secondary data gathered for a period from 2011 to 2021 using two statistical techniques, namely factor (1^{st}. principal component) analysis and Structural Equation Modelling (SEM).

It paper relies on a quantitative research methods using statically analysis to derive the variables' relationships. The research data is used is named derived/compiled data whereas data includes utilizing current data facts, frequently from various data resources, to generate original data via some kind of conversion; for example, in our paper, it is an arithmetic formula. The secondary data were collected from different sources, such reports issued by the World bank or studies conducted by some rating agencies, Fitch, and issues generated by Egyptian commercial banks and reviews of the NBE. Since it is a quantitative research, the authors follow a deductive way of reasoning as part of the research methodology.

3.1. Factor (1^{st}. principal component) analysis

3.1.1. Constructing index

Principal component analysis is used to isolate the digitalization and financial inclusion variables' components common elements. The researchers use the first principal component analysis method to build indexes of both variables. The first principal component of a set of time series dataset variables is considered simply as a linear combination of variables and constants which are selected to capture the maximum joint variation of the entire time-series as much as possible. In other words, principal component analysis is a variable reduction process. If we have dataset on multiple variables, and there is some redundancy in these variables, then it can be very useful. In this case, redundancy means that more than one variable is related to each other, possibly because of the fact that they measure the same structure. Because of this redundancy, it should be possible to isolate the discovered variables to smaller principal elements, namely artificial variables that can consequently explain most of the variation in the observed variables. These principal components can be employed to predict or standardize variables in the results analysis.

Technically speaking, the principal component may be described as a linear combination of the best-weighted observation variables. The number of components extracted using principal component analysis depends upon the number of observed variables analyzed. Principal component analysis does not make any assumptions about the underlying causal model. Principal component analysis is just a process of variable reduction, which usually leads to relatively few components that are used to explain most of the variation in a dataset of observed variables.

3.1.2. Assessment of the suitability of the data for factor analysis

Principal component analysis refers to a process of large sample. In order to obtain reliable and suitable results, the minimum number of subjects which provide usable data for the analysis should be one hundred subjects or five times the number of that variables analyzed, whichever is greater. The factors resulted from a small data set are different from those obtained using a large sample. But some authors suggest that the main focus is not on the whole sample size.

Two statistical measures additionally facilitate the evaluation of tire data decomposition: the Bartlett sphericity test (Singh et al., 2022) and the Kaiser-Meyer-Olkin (KMO) measurement of sampling adequacy (Kaiser, 1960, 1970, 1981; Kaiser & Rice, 1974). Bartlett's sphericity test must be significant (p-value is less than 0.10) to be considered an appropriate and well-constructed factor analysis. The KMO index always ranges from 0 to 1. It is recommended to use a value of 0.5 as the minimum value for a good and accepted principal component analysis (Tabachnick & Fidell, 2007; Pallant, 2005).

3.2. Structural equation Modelling (SEM)

Structural Equation Modeling (SEM) is the one of the most well-known second generation of data analysis techniques, that can be thought of as the generalization, integration, and expansion of traditional and familiar techniques such as analysis of variance (ANOVA), multiple regression analysis, and factor analysis (Hoyle, 2012). SEM enables researchers to answer a set of interrelated complex research questions in a single, systematic, and comprehensive analysis by modeling the relationships between multiple independent and dependent structures in the same time (Gefen et al., 2000). It allows researchers to estimate the relationship between observed and unobserved variables and the relationship between unobserved variables at the same time. In addition, it allows researchers to include hand-by-hand continuous and categorical observational variables and latent variables (Hoyle, 2012). Taking into account the main characteristics of this paper conceptual model, SEM is selected as the major statistical method to test the empirical model.

In the framework of structural equation modeling (SEM), unobserved variables are usually called latent variables, factors, or structures. A latent variable or factor is indirectly measured using one or more observable indicator variables that in turn reflect or form the factor. The general SEM model generally includes two forms of sub-models, namely the measurement model and the structural model. The measurement model identifies the relationship between the latent variables and the observed indicator variables. When the SEM model contains only the measurement model, it is considered a confirmatory factor analysis model. The structural model defines the relationship between latent variables and observed variables that are not indicators of latent variables (Hoyle, 1995). When the SEM model includes only the structural model, it is regarded as a path analysis model. Both confirmatory factor analysis and path analysis can be considered as special aspects of SEM.

Like path analysis, independent variables and dependent variables are called exogenous variables and endogenous variables within SEM. Exogenous variables refers to variables which affect other variables and are not affected by other endogenous variables within the model; endogenous variables represent variables that are affected by exogenous and other endogenous variables in the model. Both exogenous and endogenous variables can be observed or in specific words treated as latent variables.

Compared to other different techniques, the main advantages of structural equation modeling are that it (Collier, 2020):

1. Helps researchers to examine the influence of independent variables on several other dependent variables at the same time,
2. Allows them taking into account the measurement error, and even solving the error in the prediction relationship, and
3. Can test the entire model instead of focusing only on a single relationship. Compared a simple way to other similar techniques, such as regression (for example, only one dependent variable can be tested at a time, without considering measurement errors and focusing on individual relationships rather than overall relationships).

Following hypotheses were developed for testing by application of above-mentioned methods:

- **H1**: There is a statistically significant negative direct impact of the NBE digitalization on NBE credit risk.
- **H2**: There is a statistically significant positive indirect impact of the NBE digitalization on NBE credit risk through NBE financial inclusion.
  - ✓ **H2-1**: There is a statistically significant positive direct impact of NBE digitalization on NBE financial inclusion.
  - ✓ **H2-2**: There is a statistically significant positive direct impact of NBE financial inclusion on NBE credit risk.

Figure 1 shows the major used empirical SEM model in testing the two hypotheses of this paper, as follows:

Figure 1 represents the variables considered in the study. Independent variable is digitalization; dependent variable is credit risk; mediator variable is financial inclusion; control variables are inflation rate and population growth rate. Besides, there are direct and indirect impacts within the variables with positive or negative relationships. Based on this SEM Model, hypotheses were developed above.

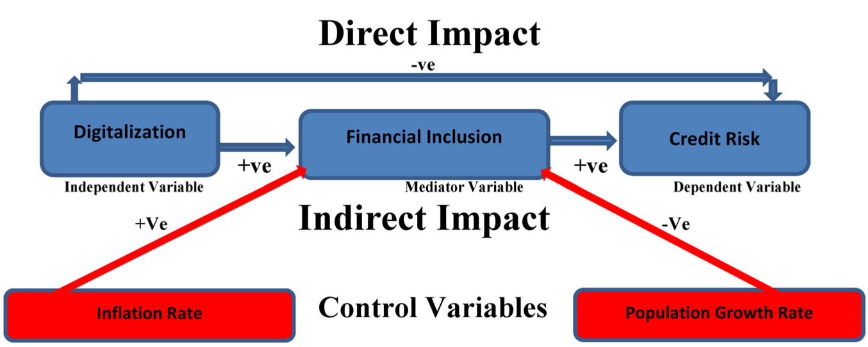

Figure 1. The general empirical SEM model.
Source: The Authors.

4. Results and discussion

4.1. Factor (1^{st}. principal component) analysis

For the empirical results of this paper, both Bartlett test and KMO are hold valid for both digitalization and financial inclusion indices, as shown in Table 1 below:

The above table reveals that the Bartlett's test of sphericity is significant with a value of .000 which is less than the significance level of 1% s. Moreover, the first principal component explains 66.2% and 74.6% respectively of the sample variation from the orthogonalized variables. Furtherly, the following Table 2 shows the resulted and automatically calculated matrix of first principal component for both resulted indices:

Thus, Digitalization and financial inclusion indices can be built using first principal component matrix in the above Table 2 depending upon the following equation:

$$\begin{aligned} \textit{Digitalization Index} =& .962 \textit{ Portable Money} \\ &+ .993 \textit{ Natural Log of Number of Loans per } 100{,}000 \textit{ Adults} \\ &+ .978 \textit{ Natural Log of Number of Credit Cards per } 100{,}000 \textit{ Adults} \end{aligned}$$

$$\begin{aligned} \textit{Financial Inclusion Index} =& .987 \textit{ Number of Branches} \\ &+ .987 \textit{ Number of Automatic Transfer Machines (ATMs)} \\ &+ .997 \textit{ Banking Services Access} \\ &+ .919 \textit{ Banking Services Usage} \\ &+ .928 \textit{ Financial Inclusion Indicator} \end{aligned}$$

Table 1. KMO and Bartlett's test to assess the factorability of the data.

KMO and Bartlett's test			
Index		Digitalization	Financial inclusion
Kaiser-Meyer-Olkin measure of sampling adequacy		.662	.746
Bartlett's test of sphericity	Approx. Chi-Square	43.074	94.224
	df	3	10
	Sig.	<.001	<.001

Source: The Authors.

Table 2. First principal component matrix.

Digitalization index Component		Weight	Financial inclusion index Component		Weight
Portable money		.962	Banking services availability	Number of branches	.987
				Number of automatic transfer machines (ATMs)	.987
Electronic debt and credit card index	Natural log of number of loans per 100,000 adults	.993	Banking services access		.997
	Natural log of number of credit cards per 100,000 adults	.978	Banking services usage		.919
			Financial inclusion indicator		.928

Source: The Authors.

4.2. Structural equation modelling (SEM)

Figure 2 demonstrates the estimation of the full structural model employed in testing the two hypotheses of this paper. Depending upon this model and the resulted statistical outputs in Tables 3 and 4, the researcher can accept the two hypotheses of the direct impact of digitalization on credit risk and that indirect one through financial inclusion.

In Table 3, the SEM results are illustrated for credit risk variable's measurement. For the direct impact of digitalization which refers to the dependent variable on it is −2.263. On the other hand, this result has a significant *p*-value (***) using 1% significance level as demonstrated in Table 4. Additionally, for the indirect impact of digitalization as independent variable's measurement upon credit risk which refers to the dependent variable with considering financial inclusion as a mediator variable is 1.396 using Table 3. This result is the sum of two standardized betas. The first one is .952 which refers to the standardized beta of the impact of digitalization as independent variable's measurement upon financial inclusion as a mediator variable in Table 4 which has a significant *p*-value (***) using 1% significance level. The second one is 1.466

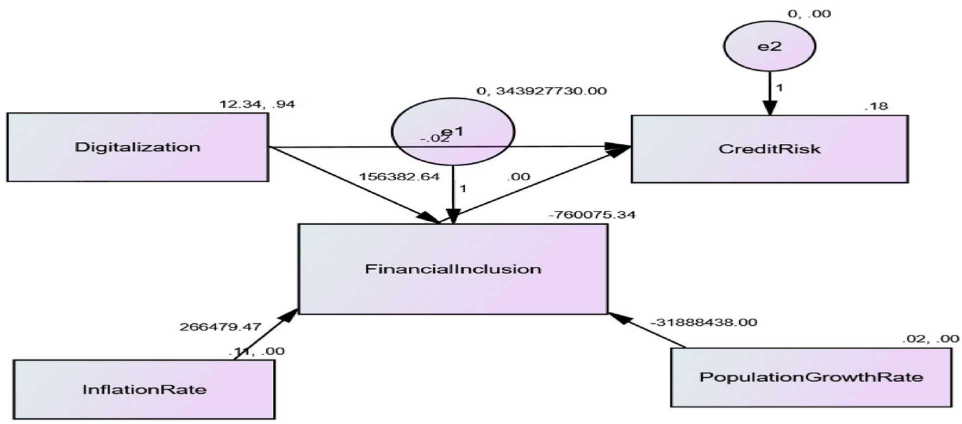

Figure 2. The estimation of SEM model.
Source: The Authors.

Table 3. SEM results.

Variables	Dependent variable	Direct effect	Indirect effect	Total effect
Digitalization	Credit risk	−2.263	1.396	−.868
Financial inclusion		1.466	.000	1.466
Inflation rate		.000	.139	.139
Population growth rate		.000	−.390	−.390

Source: The Authors.

Table 4. Regression weights.

Variable	Dependent variable	P	Standardized beta
Digitalization	Financial inclusion	***	.952
Inflation rate		.010	.095
Population growth rate		***	−.266
Digitalization	Credit risk	***	−2.263
Financial inclusion		***	1.466

Source: The Authors.

which refers to the standardized beta of the impact of financial inclusion as a mediator variable upon credit risk dependent variable in Table 4 which has a significant p-value (***) using 1% significance level. Moreover, for the total impact of digitalization as independent variable's measurement upon credit risk which refers to the dependent variable with considering financial inclusion as a mediator variable is −.868. This result is the sum of direct and indirect impacts' betas. That is −2.263 plus 1.396 in Table 3.

Thus, the researchers can accept the two hypotheses of the direct and indirect impacts considering the signs of betas. The type of mediation here is known as 'partial mediation' because of that result which holds the significance of the direct impact even after the mediator is entered to the model (Awang, 2014). Summing up, digitalization has a negative direct impact on credit risk. Also, digitalization has a positive indirect impact on credit risk through the mediator variable which is referred to as financial inclusion.

Given the fact that there are too many fitting indices, it becomes critical to determine which fit indices represent the best fit of the model (see Table 3 for a brief summary of some of the key indices shown below). This should be avoided at the whole costs, as it is basically all about removing the necessary, significant and important information under the carpet. In the over examination by McDonald and Ho (2002), it was found that the most important fitting indices frequently reported were labelled as CFI, GFI, NFI and NNFI. When deciding which indices to report, it is inherently not a wise and good practice to stick to frequently used metrics, as some of these statistics (like the GFI mentioned above) are usually used strictly for historical reasons instead of complexity. Although there are not any uniformed empirical rules to evaluate the fit of the model, it is important to report various and different indicators (Crowley & Fan, 1997). This is because of the notion that different indices reflect different model fitting aspects. Although the model of Chi Square has several connected problems, the statistics and their degrees of freedom and related p-values are still critically important and can be interpreted at any time (Hayduk et al., 2007; Kline, 2005). Hu and Bentler (1999) recently tested the threshold level, and they demonstrated a double exponential representation format. This always includes SRMR with NNFI (TLI), RMSEA or CFI. These various combinations are summarized below in Table 5.

Table 6 below shows the various fit indicators of the SEM model. The results of the chi square test show the bivariate correlation between the predictor variables and credit risk. It was found that the correlation between all predictors and stock market liquidity was neglected ($p < 0.05$). The results of chi square test which are shown in Table 6 do not confirm in any manner that the model is consistent with the observed data. The level of discovery probability is neglected ($p < 0.05$). To verify these results and recognize the weakness of the chi square test statistic established above, an additional and more robust test was done using an additional goodness of fit indicators. All other indicators in Table 6 below confirm that all the sample data fit with the model in a significant way. Only the Root Mean Squared Error Approximation (RMSEA) demonstrated a poor fit of the model. However, since most of the rest indices confirmed a model good fit, the results of the RMSEA index were neglected and were consistent with Schreiber et al. (2006, p. 327). The bottom line of this explanation is that the model fit is adequate for the data being tested.

Table 5. Hu and Bentler's two-index presentation strategy (1999).

Fit index combination	Combinational rules
NNFI (TLI) and SRMR	NNFI of 0.96 or higher and an SRMR of .09 or lower
RMSEA and SRMR	RMSEA of 0.06 or lower and a SRMR of 0.09 or lower
CFI and SRMR	CFI of .96 or higher and a SRMR of 0.09 or lower

Source: Hooper et al. (2008).

Table 6. SEM model fit indices.

Fit index	Output	Remark
Absolute fit indices		
Chi-square $\chi 2$	20.923	Reject
$p > 0.05$	P = 0.000	
Relative $\chi 2$ ($\chi 2$/df)	4.1846	Accept
RMSEA	.786	Reject
SRMR	0.593	Accept
Incremental fit indices		
NFI	.982	Accept
NNFI (TLI)	.951	Accept
CFI	.974	Accept
Parsimony fit indices		
PNFI	.934	Accept

Source: The Authors.

Table 7. Fit indices and their acceptable thresholds.

Fit index	Acceptable threshold levels	Description
Absolute fit indices		
Chi-square $\chi 2$	Low $\chi 2$ relative to degrees of freedom with an insignificant p value ($p > 0.05$)	
Relative $\chi 2$ ($\chi 2$/df)	2:1 (Tabachnick & Fidell, 2007) 3:1 (Kline, 2005) 5:2 (Wheaton et al., 1977 & Tabachnick & Fidell, 2007)	Adjusts for sample size.
RMSEA	Values less than 0.07 (Steiger, 2007)	Has a known distribution. Favors parsimony. Values less than 0.03 represent excellent fit.
GFI	Values greater than 0.95	Scaled between 0 and 1, with higher values indicating better model fit. This statistic should be used with caution.
AGFI	Values greater than 0.95	Adjusts the GFI based on the number of parameters in the model. Values can fall outside the 0-1.0 range.
RMR	Good models have small RMR (Tabachnick & Fidell, 2007)	Residual based. The average squared differences between the residuals of the sample covariances and the residuals of the estimated covariances. Unstandardized.
SRMR	SRMR less than 0.08 (Hu & Bentler, 1999)	Standardized version of the RMR. Easier to interpret due to its standardized nature.
Incremental fit indices		
NFI	Values greater than 0.95	Assesses fit relative to a baseline model which assumes no covariances between the observed variables. Has a tendency to overestimate fit in small samples.
NNFI (TLI)	Values greater than 0.95	Non-normed, values can fall outside the 0-1 range. Favors parsimony. Performs well in simulation studies (Sharma, 2005; McDonald & Marsh, 1990)
CFI	Values greater than 0.95	Normed, 0-1 range.

Source: Hooper et al. (2008).

5. Conclusion

The major goal of this research is to test the potential impact of NBE digitalization and its financial inclusion on the its credit risk. This main objective can be divided into the following two specific objectives: to test the potential direct impact of NBE digitalization on its credit risk and to investigate the potential indirect impact of NBE digitalization on its credit risk through its financial inclusion. The main result of this paper is that the NBE digitalization has both direct impact on its credit risk and indirect one through the mediator variable, namely financial inclusion (Table 7).

This study provides a main suggestion for future research, which is considering the impact of other fintech factors whether directly or indirectly by using mediators on credit risk. Moreover, this paper provides several suggestions for upcoming future research not only for digitalization, but also for financial inclusion. Firstly, the overall study can be expanded to include not only National Bank of Egypt (NBE), but also other Egyptian commercial banks. Secondly, digitalization index can be built using other components used in literature. Thirdly, financial inclusion can be built depending upon other measures used in previous studies. Fourthly, credit risk measurement can be expanded to include other measures. Fifthly, the empirical study can be examined other sectors of listed firms in the Egyptian Stock Exchange. Sixthly, the empirical study can be divided to take in its account political and other events in the Egyptian stock market including, 2011 and 2013 revolutions, 2016 Egyptian Pound floatation, and the Coronavirus disease (COVID-19) pandemic crisis happened in 2020. Finally, the bidirectional effects between each two variables of research can be examined separately using the test of Granger causality. Additionally, as part of future work directions related to this topic, this paper opens the horizon for other areas in financial digitalization and financial inclusion. For example, digital finance and corporate financing or digital financial and economic growth.

Disclosure statement

No potential conflict of interest was reported by the authors.

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