



The Recent Trends In Credit Risk Management in Banks: A Systematic Literature Review

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Abstract:

Credit risk is one of the prime risks that banks face. The purpose of this study is to find the different determinants of credit risk and different techniques that are being used in the current scenario. The time period of the study was 2018 to 2022. A systematic review of the literature was conducted based on the PRISMA methodology, and twenty-one articles were short-listed for this purpose. The articles were classified based on three themes, i.e., techniques used in the measurement of the credit risk, the region of the bank, and the determinants used to measure the credit risk. The study has implications for different parties based on the review.

Keywords: Credit risk, Measurement, PRISMA methodology, Techniques.

1. Introduction

After the global financial crisis or the 2007-2008 financial crisis, the risk management system of the banks was under the radar of the regulatory authorities. The taxonomy of the risks faced by the banks can be segregated into financial and non-financial risks. The main financial risks of the banks are credit risk, market risk, principal risk, and liquidity risk. Regulatory authorities focused on different banks' risks; the most challenging was managing the credit risk (Leo, Sharma, & Maddulety, 2019). The credit risk or the default risk is faced by the lender, i.e., the banks, if the counterparty fails to pay the obligatory amount. The uncertainty here, can be delayed payment or default in the payment, which can affect the financial health of the banks (Chance & Brooks, 2017; Pathak, 2020). The credit risk can further be segregated as consumer credit, corporate credit, credit card risk, counterparty risk, concentration risk, and collateral risk (Leo, Sharma, & Maddulety, 2019). There is growth in consumer credit which builds the importance of credit risk management. The credit risk needs to be managed to avoid any adverse impact on the banks' finance. The

management of the threat of default in the payment has evolved with time, from manual calculations to using artificial intelligence, which includes artificial neural networking, support vector machines etc. The factors considered while calculating the credit risk are the chances/probability of default, loss to be suffered if the default happens, and exposure to default. For managing the credit risk, many methods are present in front of the banks like credit scoring, pricing the risk with the help of scientific measures, quantifying the expected risk, and loan review mechanism techniques (R.B.I., 2022). Yet, the credit risk bothers the banks as the difficulties are there in the process of the assessment of the credit risk. Emerging economies like India are facing the heat of the credit risk in their banking system with recent scams of ABG shipyard scam, DHFL scam and many more. The Basel committee also issues advisories for managing the credit risk from time to time. The corona pandemic has also increased the credit risk problem in banks worldwide, and the Bank for International Settlements (BIS), in its publication in March 2022, gave observations on the governance and the practices of the credit risk. The committee also recommended working on the modelling policies of the default risk (B.I.S., 2022). The importance of measurement of the credit risk in the banking system brings to the research questions of the paper:

RQ1. What techniques are used in the different studies to measure the banks' credit risk?

RQ2. What are the different determinants used in the studies to measure the banks' credit risk?

The study is organized into different sections, where section 2 describes the methodology, section 3 covers the systematic review of the literature of 21 studies, section 4 contains the research implications, section 5 shows the limitations and future scope, and section 6 concludes the whole study.

2. Methodology

The methodology stage started with the planning of the review. In the planning stage, the need and the importance of the study is the first step. The existing literature described that credit risk is the most difficult risk to handle, and different techniques and determinants are used in different studies to measure credit risk. So, after identifying the need and the importance, the review protocol was formed. It has the details of the database from which the papers are to be selected, the keywords

to be used, and the inclusion and exclusion criteria. The next stage is performing the review, followed by reporting the review. Fig. 1 depicts the whole process:

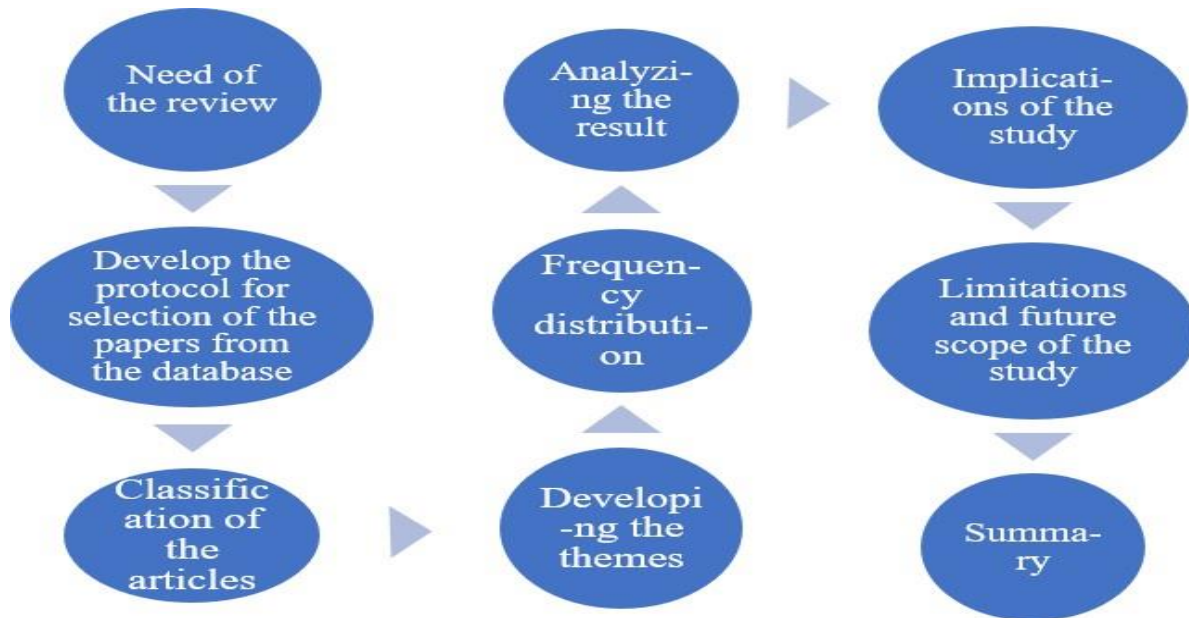


Fig.1 Process of conducting the study

For conducting the study, the PRISMA methodology was used, and the papers were selected from the Scopus database (<https://www.scopus.com/>). The keywords selected for the search were: "credit risk", "management", and "banks". A total of 1064 documents came out as the result of the search. After using the exclusion criteria based on the subject, language, keywords, the year of publication, and the publication stage, the results were limited to 104 studies. The final search term was:

TITLE-ABS-KEY ("credit risk" AND "management" AND "banks") AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018)) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (EXACTKEYWORD, "Credit Risk") OR LIMIT-TO (EXACTKEYWORD, "Risk Management") OR LIMIT-

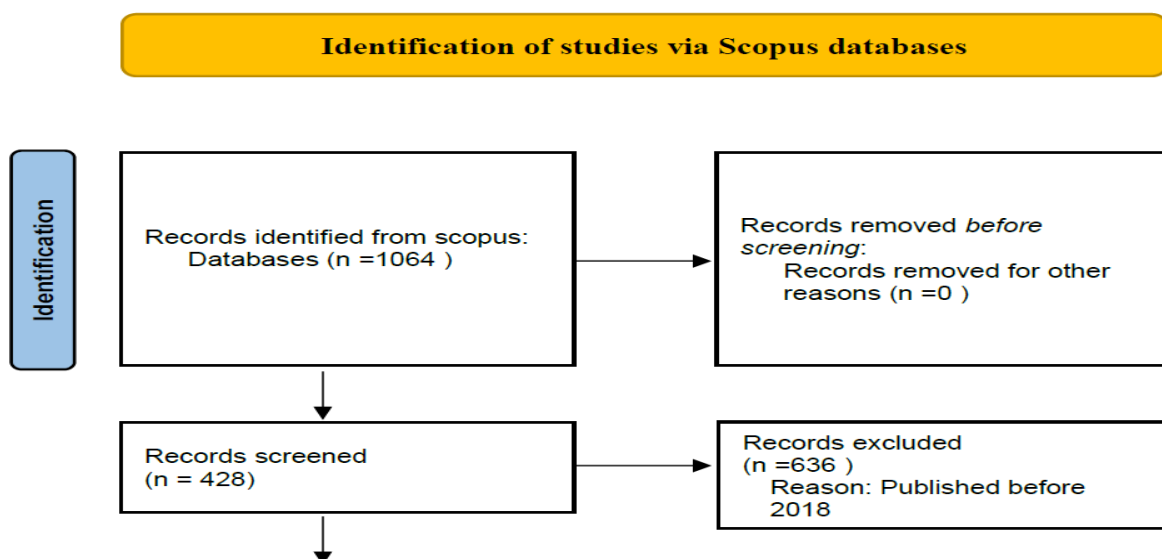
TO (EXACTKEYWORD , "Credit Risk Management") OR LIMIT-TO (EXACTKEYWORD , "Banking") OR LIMIT-TO (EXACTKEYWORD , "Risk Assessment")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")).

Based on the citations (more than five citations) and articles that were relevant to the study's scope, the suitable articles were left to 21 only. The inclusion and exclusion criteria for the study is shown in the table. 1.

Table.1 Criteria for inclusion and exclusion

Inclusion Criteria	Exclusion criteria
Must be published after 2018	Articles published before 2018
Must be related to the scope of the study, and the credit risk should be included in it.	Subject areas other than business, economics, and finance
Must be based on the banks	Articles of non-banking institutions
Must have citations more than 5	Papers presented at the conferences
Must be published in journals	Citations 5 or less than 5

Based on the criteria in table no.1, 1064 articles were first reduced to 215, then 29 and finally to 21. The PRISMA methodology is based on the inclusion and exclusion criteria shown in table 1. The diagrammatic view of the PRISMA methodology is depicted in fig. 2.



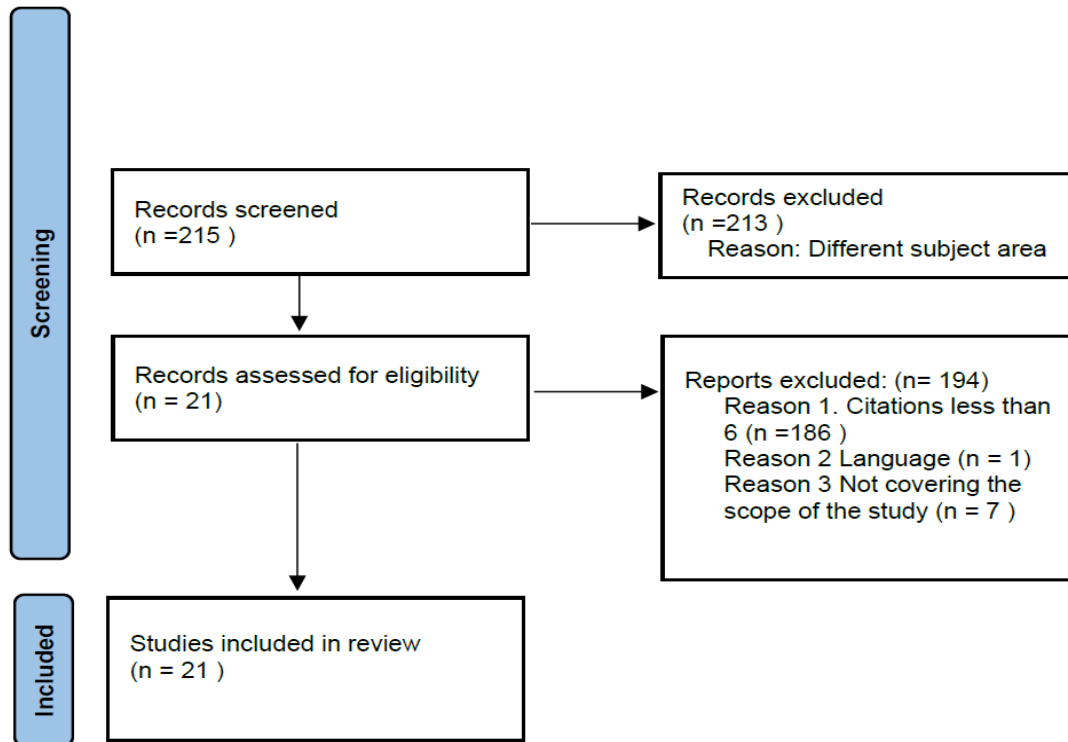


Fig.2 PRISMA Methodology (as of July 14th, 2022)

Based on the PRISMA methodology, these 21 resultant studies were taken to conduct systematic review of the literature.

3. Outcomes of the SLR

3.1 Classification of studies

The studies have been classified into three themes; where the first theme deals with the classification based on the techniques used in the articles. The statistical technique consists of 13 articles out of 21 studies (62%), machine learning consists of 5 articles out of 21 (24%), and internal rating-based articles are 3 out of 21 (14%). In the second theme, the classification is done on the bank's region and religion (if any). Islamic banks are 3 out of 21 (14%), Asian banks are 10 out of 21 (48%), European banks are 4 out of 21 (19%), and the rest of the world banks are 6 out of 21 (28%). In the third theme, the classification is done on the basis of the

determinants used to measure the credit risk of the banks. Out of all the determinants, the main are capital adequacy ratio, Gdp growth rate, bank asset quality, loan loss provision, loan quality, asset quality, and NPA. These classifications based on different themes are shown in table 2, table 3, and table 4.

Table. 2 Classification of the studies based on techniques used

No.	Total	Theme	Statistical Technique (n=13)	Machine Learning (n=5)	Internal-Rating based (n=3)
		Classification of the studies based on techniques used to measure credit risk	(Elbadry, 2018)	(Leo et al., 2019)	(Cucinelli et al., 2018)
			(Jabbouri & Naili, 2019)	(Teng & Lee, 2019)	(Wang et al., 2020)
			(Akram & Rahman, 2018)	(Srinivasan & Kamlakannan, 2018)	(Montes et al., 2018)
			(Chamberlain et al., 2020)	(Khemakhem et al., 2018)	
			(Dang, 2019)	(Tang et al., 2018)	
			(Rehman et al., 2019)		
			(Sharifi et al., 2018)		
			(Ozili, 2020)		
			(Wahab, 2018)		
			(Roeder et al., 2022)		
			(Lambert et al., 2019)		
			(Moudud-ul-huq et al., 2020)		
			(Duho et al., 2020)		

Table. 3 Classification of the articles based on the Bank's region.

No.	Theme	Islamic Banks (n=3)	European Banks (n=4)	Asian Banks (n=10)	Rest of the world (n=6)
2.	Classification of the articles based on the banks' continent and religion based (if any)	(Akram & Rahman, 2018) (Chamberlain et al., 2020) (Wahab, 2018)	(Ozili, 2020) (Lambert et al., 2019) (Montes et al., 2018) (Cucinelli et al., 2018)	(Rehman et al., 2019) (Dang, 2019) (Sharifi et al., 2018) (Moudud-ul-huq et al., 2020) (Teng & Lee, 2019) (Srinivasan & Kamlakannan, 2018) (Wang et al., 2020) (Tang et al., 2018) (Akram & Rahman, 2018) (Chamberlain et al., 2020)	(Leo et al., 2019) (Jabbouri & Naili, 2019) (Elbadry, 2018) (Roeder et al., 2022) (Khemakhem et al., 2018) (Duho et al., 2020)

Table. 4 Classification of the studies based on the determinants of credit risk.

No.	Theme	Loan Quality (n=5)	Bank Asset Quality (n=4)	Capital Adequacy Ratio (n=6)	Loan Loss Provisi-on (n=5)	Diversi-fication (n=1)	Corpor-ate Govern-ance (n=1)	NPA (n=3)
3.	Classificatio n of the studies based on the determinants of credit risk.	(Akra m & Rahm an, 2018) (Dang, 2019) (Ozili, 2020) (Jabbo uri & Naili, 2019) (Elbad ry, 2018)	(Akram & Rahman, 2018) (Wahab, 2018) (Wang et al., 2020) (Lamb-ert et al., 2019)	(Waha b, 2018) (Rehm an et al.,201 9) (Ozili, 2020) (Jabbo uri & Naili, 2019) (Elbadr y, 2018) (Cham berlain et al., 2020)	(Wahab, 2018) (Dang, 2019) (Moudud-ul-huq et al., 2020) (Lambert et al., 2019) (Elbadry, 2018)	(Rehman et al.,2019)	(Rehm-an et al.,2019)	(Sharifi et al., 2018) (Moudud -ul-huq et al., 2020) (Jabbou-ri & Naili, 2019)

		EBIT-DA (n=2)	Debt Service Coverage Ratio (n=1)	Debt Ratio (n=3)	GDP Growth Rate (n=4)	Corporate Loan (n=1)	Internal Rating Based (n=2)	Profitability (n=2)
		(Wang et al., 2020) (Ozili, 2020)	(Wang et al., 2020)	(Wang et al., 2020) (Elbadry, 2018) (Chamberlain et al., 2020)	(Moududul-huq et al., 2020) (Ozili, 2020) (Lambert et al., 2019) (Jabbouri & Naili, 2019)	(Lambert et al., 2019)	(Cucine lli et al., 2018) (Montes et al., 2018)	(Jabbouri & Naili, 2019) (Chamberlain et al., 2020)

3.2 Thematic Results

3.2.1. Techniques used

(Leo et al., 2019) (Teng & Lee, 2019) (Srinivasan & Kamlakannan, 2018) (Khemakhem et al., 2018) (Tang et al., 2018) focused on the use of machine learning techniques and mostly used machine learning techniques were support vector machines, artificial neural networks, and decision tree. (Khemakhem et al., 2018) combined artificial neural network with the support vector machine and were better than the results of these two techniques individually, but (Teng & Lee, 2019) in their study found that the decision tree provides better results than the other techniques present in machine learning.

(Cucinelli et al., 2018) (Wang et al., 2020) (Montes et al., 2018) focused on the internal rating-based (IRB) techniques and recommended the implication of the BASEL-II norms to control credit risk. (Elbadry, 2018) (Jabbouri & Naili, 2019) (Akram & Rahman, 2018) (Chamberlain et al., 2020) (Dang, 2019) (Rehman et al., 2019) (Sharifi et al., 2018) (Ozili, 2020) (Wahab, 2018) (Roeder et al., 2022) (Lambert et al., 2019) (Moudud-ul-huq et al., 2020) (Duho et al., 2020) also supported the results of IRB technique using the statistical techniques.

3.2.2 Region of the study

More studies are conducted in the Asian banks in which Chinese banks have most of the studies. (Akram & Rahman, 2018) (Chamberlain et al., 2020) (Wahab, 2018) did their studies on Islamic banks and found that the credit risk is less in Islamic banks as compared to commercial banks. (Montes et al., 2018) (Cucinelli et al., 2018) did their studies on the European banks taking the IRB approach. In the rest of the world, most of the studies focus on the African continent (Duho et al., 2020) (Jabbouri & Naili, 2019).

3.2.3. Determinants of Credit risk

(Wahab, 2018) (Rehman et al., 2019) (Ozili, 2020) (Jabbouri & Naili, 2019) (Elbadry, 2018) (Chamberlain et al., 2020) in their studies, found that the capital adequacy ratio is one of the vital determinants of the credit risk. (Wahab, 2018) (Dang, 2019) (Moudud-ul-huq et al., 2020) (Lambert et al., 2019) (Elbadry, 2018) (Akram & Rahman, 2018) (Ozili, 2020) gave emphasis on the loss loan provision, and loan quality for the measurement of the credit risk, but (Rehm-an et al., 2019) proved in his study that corporate governance is most important to measure the credit risk as it can reduce the credit risk with its presence.

3.3 Citations

The most cited article is by (Leo et al., 2019), which has been cited 71 times, followed by (Tang et al., 2018) 26 times, and (Dang, 2019) (Cucinelli et al., 2018) 20 times each. All of these are related to different techniques, which shows that the work on credit risk is being done in different fields. (Leo et al., 2019) (Tang et al., 2018) have the majority percentage of the citations. Their work is on machine learning which is the essence of today's banking sector. The citations show that the work done on the Asian and European banks is more focused upon rather than on the

Islamic banks. The citation graph is shown in fig. 3. in which the names of the authors are on the y-axis, and the number of citations is on the x-axis.

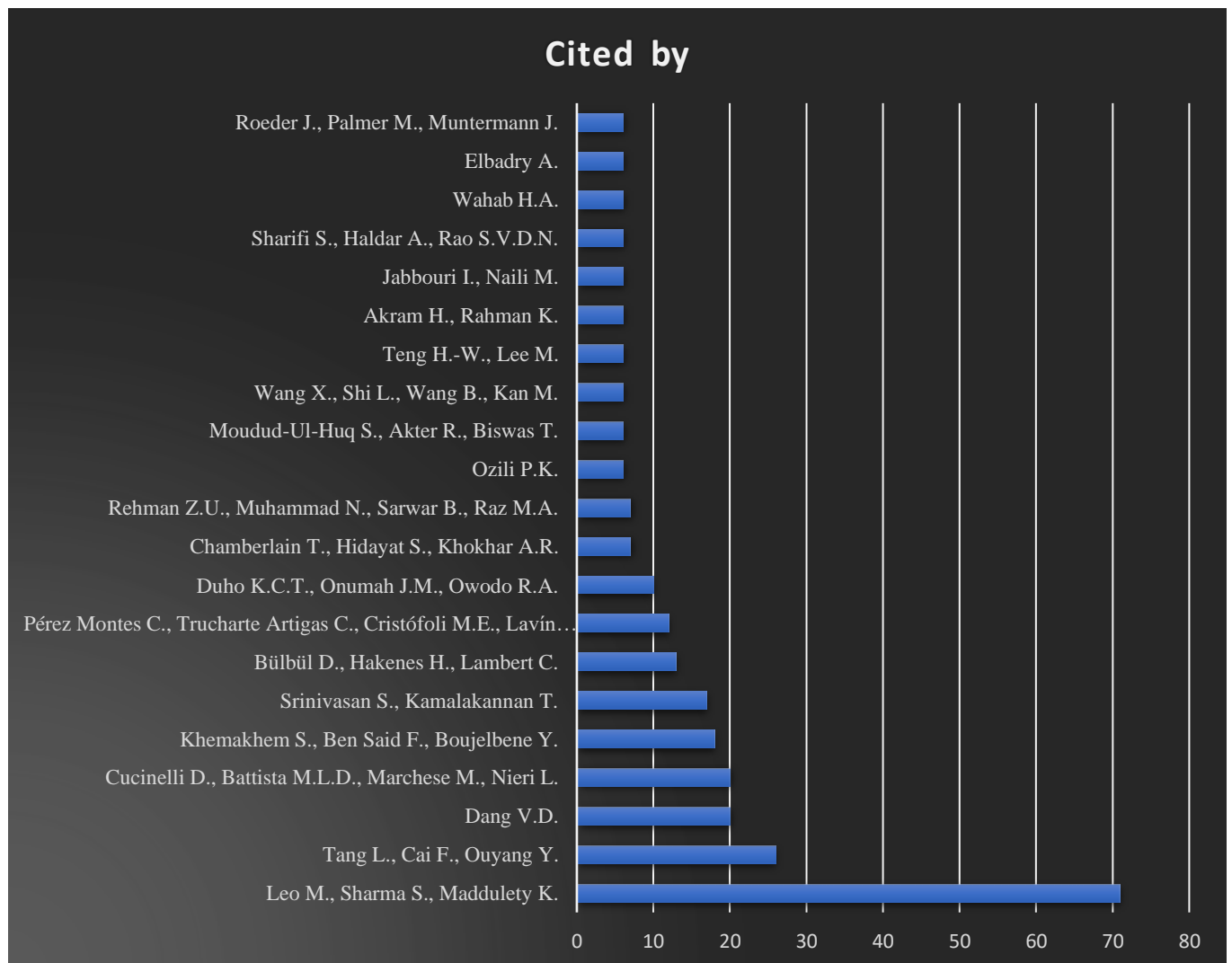


Fig.3 Citations of the articles.

3.4 Journals

(Chamberlain et al., 2020) studied the difference in credit risk between the Islamic banks and commercial banks, and they found that the Islamic banks manage the credit risk well. (Elbadry,

2018) stated in his study on Saudi's 12 banks found that CAR has a negative effect on credit risk. These two articles were published in the Journal of Islamic Accounting and Business Research. The research articles of this journal focus on Islamic banking and Islamic countries (Lambert et al., 2019) proved in their study that the banks go for the use of advanced credit risk management systems when they see high competition and sector conformation. (Montes et al., 2018) in their paper focused on IRB and showed that the capital saving could not be attributed to the improved risk measurement techniques. These two articles were published in the Journal of Financial stability. Table 5 shows the distribution of the articles based on the journals they are published in.

Table 5. List of journals

Journal	Articles	% of total
Journal of Financial Stability	2	9.52
Journal of Islamic Accounting and Business Research	2	9.52
Review of Pacific Basin Financial Markets and Policies	2	9.52
Risks	1	4.76
Technological Forecasting and Social Change	1	4.76
Management Science Letters	1	4.76
Journal of Banking and Finance	1	4.76
Journal of Modelling in Management	1	4.76
Computational Economics	1	4.76
International Journal of Managerial Finance	1	4.76
Financial Innovation	1	4.76
Journal of Financial Economic Policy	1	4.76
FIIB Business Review	1	4.76
Engineering, Construction and Architectural Management	1	4.76
ISRA International Journal of Islamic Finance	1	4.76
Managerial Finance	1	4.76
Journal of Social Sciences Research	1	4.76
Decision Support Systems	1	4.76
Total	21	100.00

3. Study Implications

There are many implications of the study for the different parties interested. *First*, for the academicians, this study offers the different techniques that are being used for the purpose of measuring credit risk. Islamic banks have less credit risk as compared to commercial banks can be an area of study for them. *Second*, the banking regulatory authorities can see that the process of controlling the credit risk demands sound techniques and good corporate governance. *Third*, the governments need to work on the BASEL norms implication so as to manage the credit risk of the banks. It is found in the studies that the norms are required to be implemented in a better way.

4. Limitations and Future scope of the study

The *study's limitations* are that it only consists of articles from one database. Other databases, like Web of Science, and Google Scholars, can also be considered. The inclusion and exclusion criteria can also take non-banking financial institutions into consideration, as the credit risk of both institutions is nearly the same. The time period of the study can also be increased so as to take more papers into account.

The *future scope* for further studies, derived from the articles, *first* can be the Islamic banking system compared to the commercial banking system. Work can be done to find the exact reasons why Islamic banks have less credit risk compared to commercial banks. *Another future scope* offers work on corporate governance, and credit risk as only one study out of the 21 studies has taken into consideration the corporate governance variable in it, which proved to be the most efficient in managing the credit risk. Work on the machine learning techniques can also work as a literature gap when included with any of these two areas.

5. Conclusion

The study was conducted to see the techniques that are being used to measure the credit risk and the determinants to measure the credit risk. Based on the criteria, only 21 articles were short-listed for the review. The study was conducted in a planned manner, and the PRISMA methodology was used. The articles were classified based on the techniques used to measure the credit risk, the region of the banks in the study, and the determinants to measure the credit risk. This study also had implications for academicians, bank regulatory authorities, and governments. BASEL norms and the guidelines issued are to be looked upon timely so that the credit risk can be managed.

Further work needs to be done on Islamic banking and the impact of corporate governance on the management of credit risk.

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