How Fintech Innovations and Financial Inclusion Can Impact Loan Business Cycle

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ABSTRACT

New technologies and new business models are changing traditional banking business model, and the trend also has impact on loan's product cycle. This leads to the key research question of the paper what is the impact of financial inclusion and fintech on loan's product cycle. To address the research question the study performs a descriptive qualitative analysis, by adopting a document reviewing approach. The study explores the impact of fintech innovations and fintech inclusion on the loan product cycle through its three main phases. Analyzing the loan credit cycle is particularly important, especially in the era of digital transformation for to give insight to resource allocation strategies and financial behaviors of large-scale economies undergoing fast development. Banks could use AI models for to offer suitable loans to customers based on likelihood of borrower's default. A lot of researchers found explainable AI (XAI) better suited for credit risk models, with SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) as the most suited ones.

Key words: *Banks, Fintech innovations, Financial inclusion, Credit risk* , *Bank loans*

I. INTRODUCTION

New technologies and new business models are changing traditional banking business model, and the trend also has impact on loan's product cycle. This leads to the key research question of the paper what is the impact of financial inclusion and fintech on credit loan's product cycle. To address the research question the study performs a descriptive qualitative analysis, by adopting a document reviewing approach. The study explores the impact of fintech innovations and fintech inclusion on the loan product cycle through its three main phases: (I) origination, (II) management, and (III) collection. A huge body of research analyze the impact of financial innovations and financial inclusion on different stages of the loan product cycle, related mainly to probability of default, loss given default, non-performing loans (NPLs) or recovery rates. The significance of this study is to review and analyze the impact of finance innovations and financial inclusion through the whole loan product cycle.

I.A. Credit risk overview

Credit risk is defined as the risk arising of default by obligor on its obligation, or an increased probability of default or related to rating downgrade. Some of the variables related to relative credit risk assessment are:

- Obligor's capacity and willingness to pay
- External conditions
- Credit risk mitigants, etc.

In general, it is expected a bank to incur losses due to their lending business. Such losses, seen as an inevitable cost of doing business, are called expected losses. Expected loss (EL) is the average loss level encompassing long-term range of representative economic conditions, and not based on the economic cycle. They are statistically calculated despite the fact that their average amount could variate on a yearly basis. In addition, expected loss should be adequately incorporated in loan pricing. The three components that determine EL are:

- Probability of default (PD): the probability of default by borrower before the maturity of the loan facility

Probability of default (PD): is commonly related to the borrower's risk rating. It is a borrower-specific estimate, calculated independently from the credit facility's properties. Transition or migration matrices are used to model the changing nature of probability of default, as the second year PD is assumed to be higher than the first year PD. In general, banks calculate corporate PDs on the ground of long-run default rates based on average of issuer-weighted historical default rates, while for retail lending they use a 12-month point-in-time probability-weighted PD (as presented in Table 1). In addition, it is estimated the correlation of default rates to forward-looking macroeconomic variables, and more particularly industry and country specific.

Table 1 Probability of default
Source: HSBC, 2024

	Wholesale lending and derivatives		Retail lending	
	Internal credit rating	12-month Basel probability of default %	Internal credit rating	12-month probability weighted PD %
Quality classification				
Strong	CRR 1 to CRR 2	0–0.169	Band 1 and 2	0.000–0.500
Good	CRR 3	0.170–0.740	Band 3	0.501–1.500
Satisfactory	CRR 4 to CRR 5	0.741–4.914	Band 34 and 5	0.501–1.500
Sub-standard	CRR 6 to CRR 8	4.915–99.999	Band 6	20.001–99.999
Credit-impaired	CRR 9 to CRR 10	100	Band 7	100

- Exposure at default (EAD): the bank's credit exposure amount to a customer or a counterparty at the time of default

Exposure at default can be very distinct from the owing amounts at the initiation of the lending facility. This problem is particularly exuberated with derivatives, which requires Monte Carlo simulations for its quantification.

- Loss given default (LGD): the fraction of EAD that is lost in the event of default

In the event of default LGD incorporates all the costs incurred in relation to the collection and sale of the collateral, as well industry and country specific factors.

Worldwide LGD spiked during 2007-2008 financial crisis presented in Figure 1. The macroeconomic impact on LGD for mortgage portfolios is modelled based on estimated loan-to-value measures for the remaining maturity of the facility by utilizing national level house price index forecasts (HSBC, 2024).

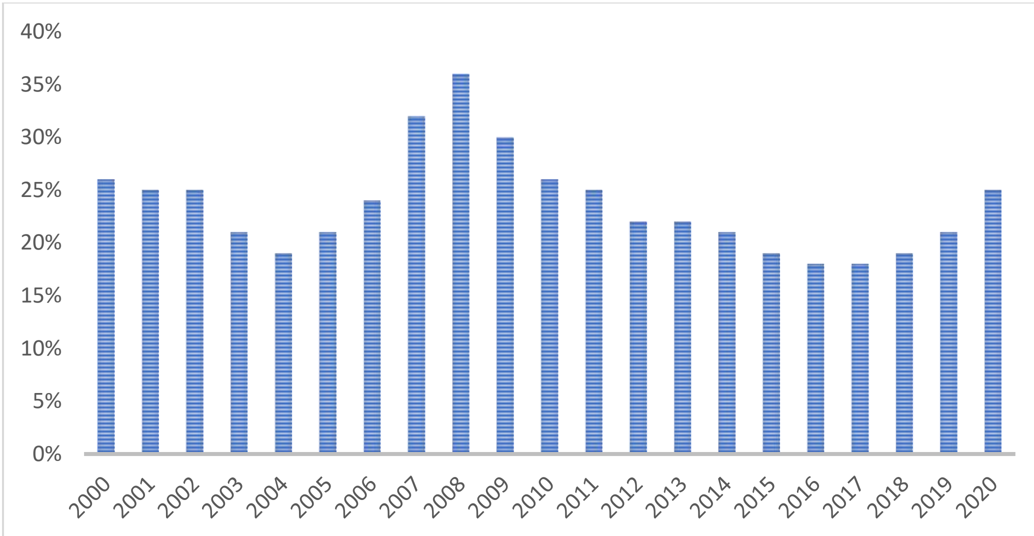

Figure 1 Worldwide discounted LGD
Source: Global Credit Data, 2023

In the event of default, the expected loss can be defined as:

$$EL = PD*EAD*LGD \qquad \text{(Formula 1)}$$

I.B. Literature observation

Up-to-date there is a big stake of studies exploring the relation between fintech and banks' risk taking related particularly to China (Fang et al., 2023; Hu et al., 2022; Deng et al., 2021). A balance sheet lending activity by fintechs have negative effect on commercial banks' risk taking, whereas a peer-to-peer (P2P) business model has adverse effect on cooperative banks, mostly related in both cases with decline in profitability (Elekdag et al., 2024). Fang et al. (2023) find that the increase in fintech trigger banks' risk taking through liquidity creation. Liberti & Petersen (2019), Jakšič & Marinč (2018), and Mild et al. (2015) argue that some important qualitative data is not thoroughly utilized in fintechs' credit models. As per Bakker et al. (2023) the increase in fintech volumes boosts banking competition and decreases lending spreads in Latin America. Grennan & Michaely (2021), Deng at al. (2021), Yeo & Jun (2020), and FSB (2017) find that information asymmetry in credit markets is reduced through fintech lending. Partnerships with fintech or fintech inclusion reduces banks' risk taking through diversification, efficiency and transparency (Daud et al., 2022; Murinde et al., 2022; Hu et al., 2022; Campanella et al., 2017). Fintech has positive effect on the stability of financial institutions in emerging markets, while it decreases the stability of financial institutions in developed markets (Fung et al., 2020). Large commercial banks profit from cooperation with P2P platforms, while P2P lending has negative effect on cooperative banks (Ben Naceur at al., 2023). Fintech has higher negative impact on financial institutions in countries with more advanced financial systems (Ben Naceur at al., 2023). Balance sheet lending, that more closely resemble traditional banking business model, has negative impact on banks' profitability and is leading to an increase risk taking (Ben Naceur et al., 2023). Investing in financial innovation can mitigate some of the negative impacts from fintech (Chen et al., 2019), as well improve operational efficiency (Wang et al., 2021), and increase the lending to small and medium enterprises (Lin & Dong, 2024). In comparison to banking industry, fintech lending platforms are 20 percent faster in application processing (Fuster et al., 2019). Fintech negative impact on banks' profitability is due to increased costs incurred by banks mainly related to investment in new technologies and reduced interest income appertaining to severe competition with fintech companies (Ben Naceur et al., 2023). The negative effect on banks' profitability is associated in markets with higher credit depth, higher stock market turnover, lower bank concentration and higher commercial banks' profitability (Ben Naceur et al., 2023). The adverse effect on banks' profitability is more closely associated to banks with a lower risk profile, lower non-performing loans (NPLs), and lower probability of insolvency (Ben Naceur et al., 2023). Fintech lending shares increase mainly in markets with higher loan denial rates and lower consumer credit scores (Jagtiani et al., 2021). Increase in fintech transactions has a positive effect on banks' non-interest income, but not enough to counterbalance the negative effect of fintech competition on banks' profitability (Ben Naceur et al., 2023). An increase in P2P and balance sheet lending leads to decease in ROE of cooperative banks (Ben Naceur et al., 2023). The increase of balance sheet lending leads to a decrease in commercial banks' NIM (Ben Naceur et al., 2023). Fintech adoption by banks reduces their credit risk (Zhang et al., 2023). Z-score of commercial banks in general is lower in comparison to z-score of cooperative banks (Elekdag et al., 2024). The increase of fintech volumes in general leads to increase banking risk taking (Elekdag et al., 2024). Some smaller cooperative banks may lose some young tech savvy customers, due to the lack of enough sources to invest in digitalization (Coelho et al., 2019).

II. METHODOLOGY

This study performs a descriptive qualitative analysis, by adopting a literature review approach and a refined data analysis for to obtain valuable outcomes. The data used for this study was gathered from various sources, mainly retrieved from ScienceDirect and Google Scholar including relevant journals, banking annual financial reports (HSBC, Deutsche Bank, Banco Santander, etc.), related books, and newspapers and various official public data. Data was first examined and interpreted in order to gain an in-depth understanding and obtain contextual meaning for a reliable and valid research and then analyzed and synthesized. A literature review on the impact of fintech on bank risk taking due to the fact that fintech and big tech companies take a big stake in credit loans to small and medium enterprises and unserved or underserved population. Fintech and big tech companies employ big analytics like machine learning (ML) and artificial intelligence (AI) in the credit loan models. This analysis could shed light on the better comprehension of the usage of ML and AI models in credit loan product cycle. Further, selected banks' annual reports were investigated for credit model usage and compared with the research findings on the topic.

III. ANALYSIS and FINDINGS

Worldwide the retail banking clients with an account in financial institution increased from 50.63 percent in 2011 to 73.97 percent in 2021 (as presented in Figure 2). 98.51 percent of the population in Euro area has an account in financial institution, which is the highest worldwide (as presented in Figure 2). In comparison only 38.94 percent of the population in Arab world hold an account in financial institution, which is the lowest percent (as presented in Figure 2).

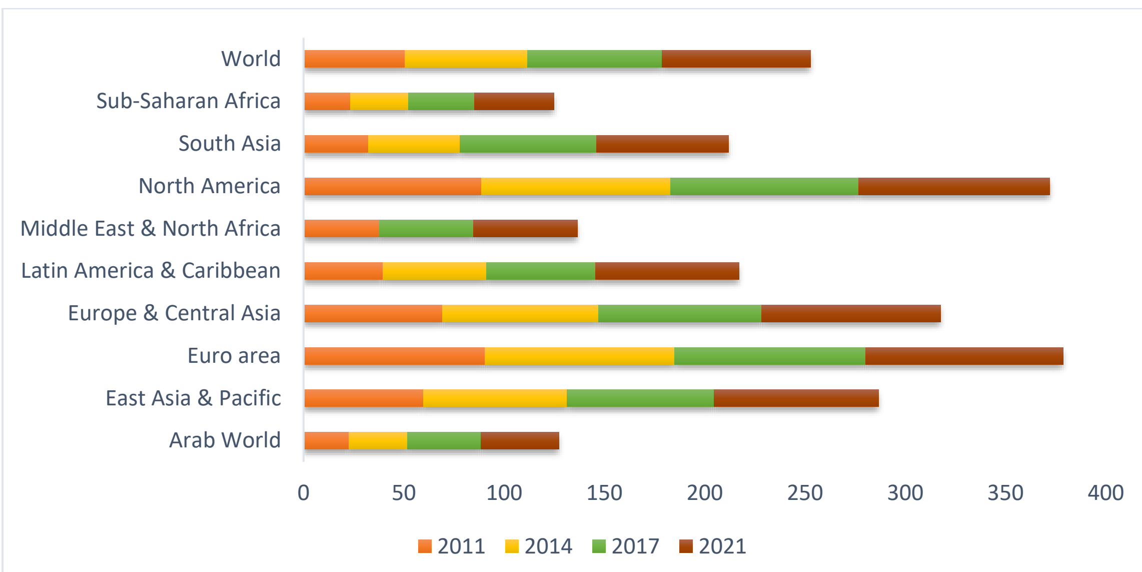

Figure 2 Retail clients with financial institution account (% age 15+)
Source: World Bank DataBank, 2024

In contrast, to the retail clients' account at a financial institution, the mobile accounts worldwide were at very low level or 10.24 percent in 2021 (presented in Table 2). The highest number with a mobile money accounts in 2021 are retail clients in labor force or 16.55 percent, while the lowest number were at retail clients with primary education or less or 5.72 percent for the same period (presented in Table 2).

Table 2 Mobile money accounts worldwide
Source: World Bank DataBank, 2024

Mobile money account	2014	2017	2021
Mobile money account (% age 15+)	2.06	4.35	10.24
Mobile money account, in labor force (% age 15+)	2.47	5.3	16.55
Mobile money account, income, poorest 40% (% ages 15+)	1.3	2.75	6.81
Mobile money account, income, richest 60% (% ages 15+)	2.56	5.43	12.53
Mobile money account, out of labor force (% age 15+)	1.38	2.68	7.69
Mobile money account, primary education or less (% ages 15+)	1.78	2.72	5.72
Mobile money account, young (% ages 15-24)	2.71	6.34	14.26

Worldwide the retail clients, borrowed from a formal financial institution, increased from 9.29 percent in 2011 to 28.38 percent in 2021 (as presented in Figure 3). The highest number of retail clients borrowed from a formal financial institution worldwide in 2021 is in North America or 67.77 percent, while in Sub-Saharan Africa and Arab World is only 9.81 and 9.87 percent respectively for the same period (presented in Figure 3).

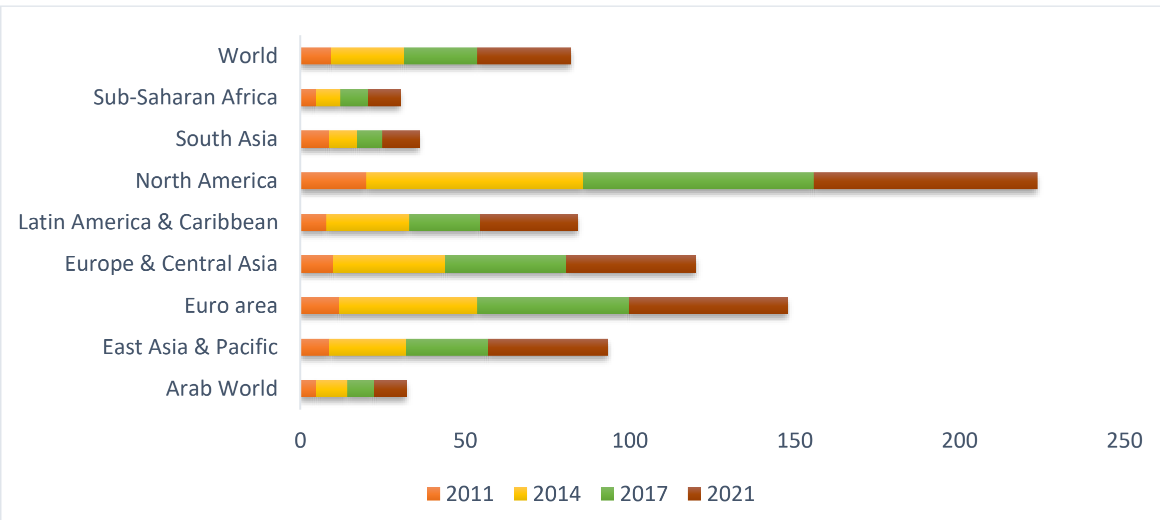

Figure 3 Borrowed from a formal financial institution (% age 15+)
Source: World Bank DataBank, 2024

In general, bank loan products aim to support businesses to expand, invest, grow or cover short-term working capital needs and also to enhance consumer spending through loans for homes, cars and other goods. Worldwide the retail clients, owning a credit card from a formal financial institution, increased from 14.94 percent in 2011 to 24.48 percent in 2021 (as presented in Figure 4). The highest number of retail clients owning a credit card from a formal financial institution worldwide in 2021 is in North America or 68.4 percent, while in Sub-Saharan Africa and South Asia is only 3.45 and 3.74 percent respectively for the same period (presented in Figure 4).

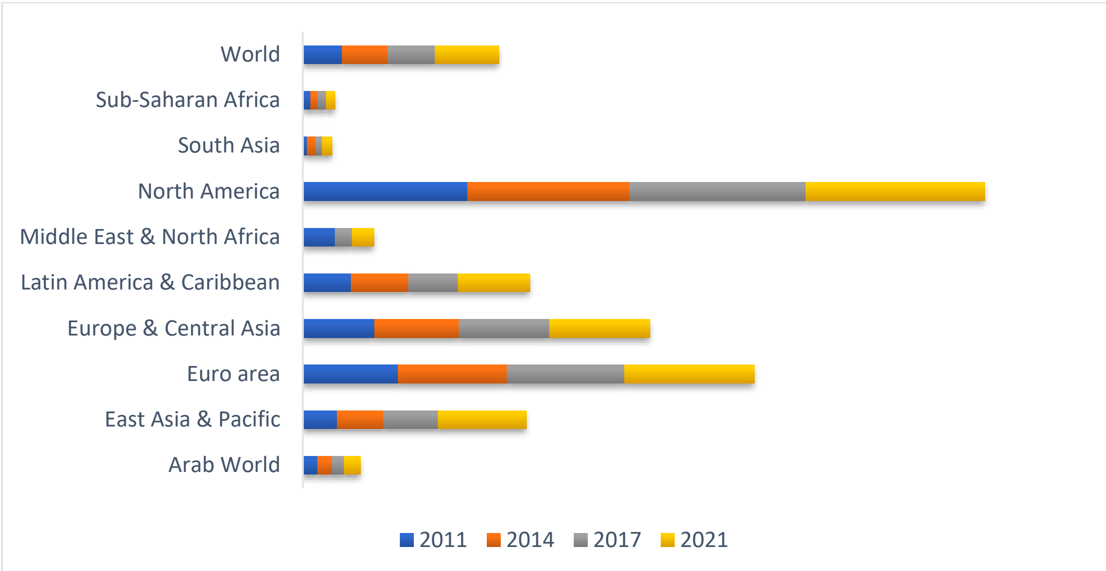

Figure 4 Owns a credit card (% age 15+)
Source: World Bank DataBank, 2024

Developed credit markets are essential for a long-term prosperity, but at the same time unrestricted lending growth could bring negative effects on the financial system and the broader economy as well (Giraldo et al., 2024). Business cycle fluctuations are influenced from lending growth and loan loss provisions. Analyzing the loan credit cycle is particularly important, especially in the era of digital transformation for to give insight to better resource allocation strategies and predicting financial behaviors of large-scale economies undergoing fast development.

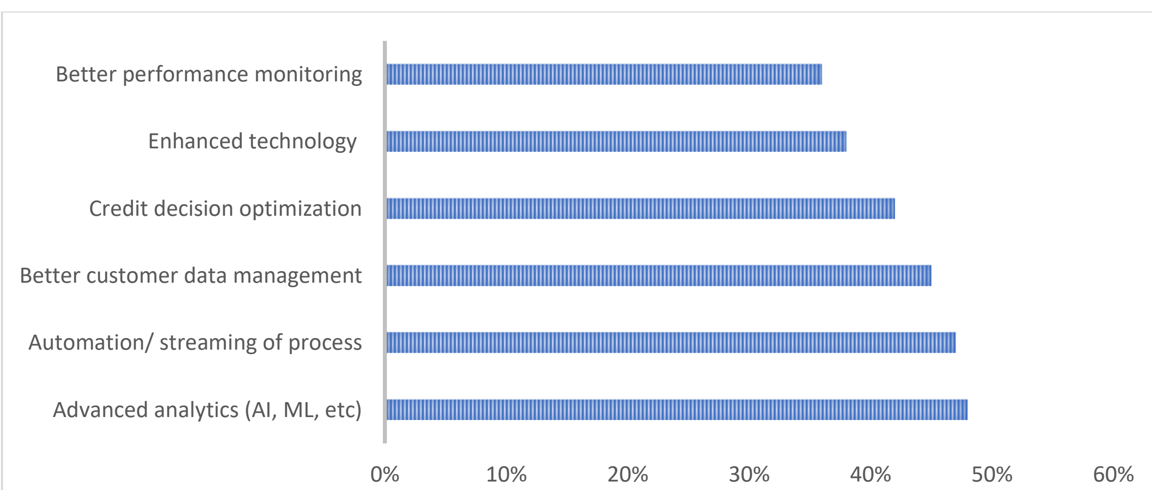

Figure 5 Most challenging area of transformation
Source: GARP & SAS, 2022

Banks are going under credit risk transformation process, mainly due to optimization of credit origination, the ground block for business growth (GARP & SAS, 2022). Advanced analytics as AI and ML is the most challenging area for transformation followed by automation and streaming of processes (presented in Figure 5). The use of advanced analytics for credit risk is falling behind in comparison to AI/ML usage for other banking functions or businesses (GARP & SAS, 2022).

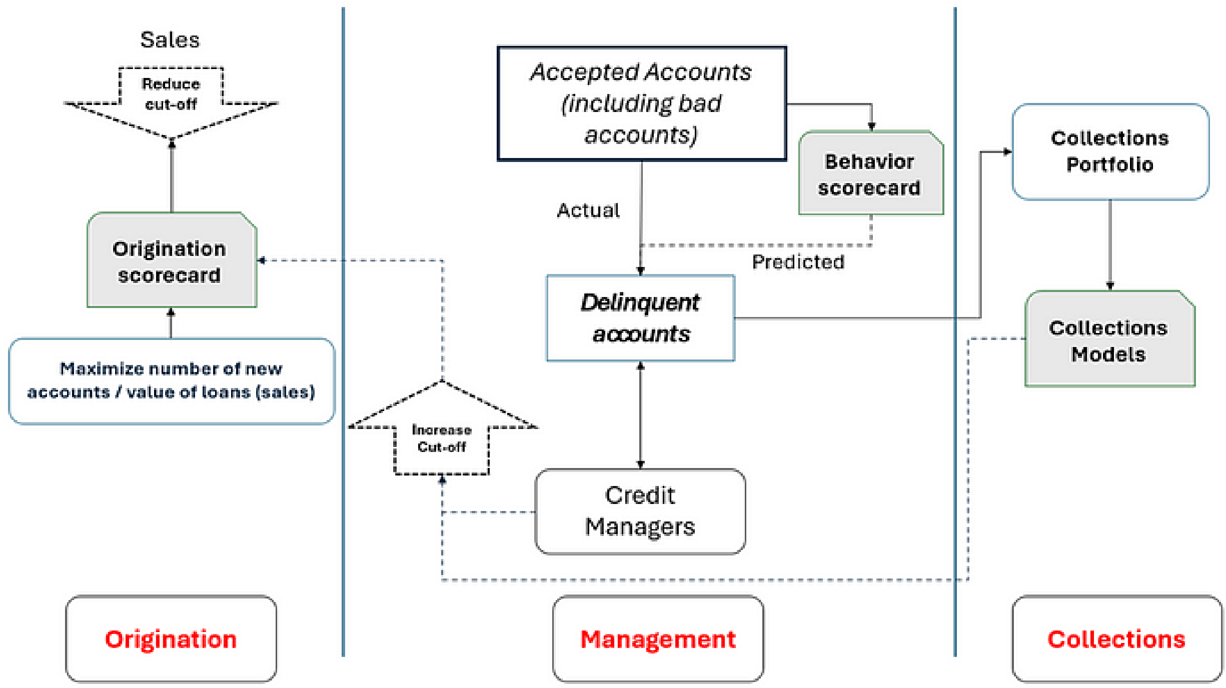

Figure 6 Bank credit loan business cycle
Source: Refaat, 2024

Credit loan product' cycle comprises three main phases: (I) origination, (II) management, and (III) collection (presented in Figure 6). In the origination phase, banks could use AI "origination scorecard" model for to offer suitable loans to customers based on likelihood of borrower's default (Refaat, 2024). In general, once the credit is approved it moves to the second phase of management by portfolio management division, which in terms also could utilize AI performance models for to improve the management process. In case of default, the credit facility enters the third phase; collections, where AI models can be utilized for to predict the likelihood of recovery and collection.

Phase I of credit loan business cycle

Scoring systems are performing automatic evaluation of loan applications without the need of an analyst, by automatically assigning to a retail client an individual score used for subsequent decision (Banco Santander, 2024). Credit scoring enables banks to preclude from onboarding risky clients, reduce costs, etc. In general, for scoring retail clients there are three types of models: credit bureau scores, pooled models and custom models (Crouhy et al., 2013). The capabilities of a scoring system can worsen over time due to a change of the underlying population or to the behavior of the population. Further, credit rating an ordinal estimate of the probability of default, is seen as an instrument that distinguish between traditional and modern credit risk management (De Laurentis et al., 2010). Good credit rating model should possess the following features:

- Specificity: computing the distance from default event with exclusion of other financial properties not directly related to it
- measurability and verifiability: a credit score should provide an appropriate presumption about possible default event
- objectivity and homogeneity: comparability between portfolios and establish judgments only based on credit risk factors

From Table 3 can be drown some basic conclusions:

- In case of a homogenous population the actual frequencies converge to the central probability in a long run
- As a consequence from the first statement, it could be stated that central probabilities could be forecasted based on actual frequencies

Table 3 Excerpt average cumulated annual default rates per issues cohorts (1998-2007) end of year %
Source: De Laurentis et al., 2010 (initially from: Moody's 2008)

Initial Rating	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
A1	0	0	0	0	0.04	0.06	0.06	0.06	0.06	0.06
A2	0.05	0.11	0.25	0.35	0.46	0.52	0.52	0.52	0.52	0.52
A3	0.05	0.19	0.33	0.43	0.52	0.54	0.54	0.54	0.54	0.54
B1	1.71	5.76	10.21	14.07	17.14	19.59	21.21	23.75	26.61	28.37
B2	3.89	8.85	13.69	18.07	20.57	23.06	26.47	28.52	30.51	32.42
B3	6.18	13.24	21.02	27.63	33.35	39.09	42.57	45.19	48.76	51.11
Caa2	18.98	29.51	37.24	42.71	44.99	46.83	46.83	46.83	46.83	46.83
Caa3	25.54	36.94	44.01	48.83	54.04	54.38	54.38	54.38	54.38	54.38
Ca-C	38.28	50.33	59.55	62.49	65.64	66.26	66.26	66.26	66.26	100

In the past, credit rating models were assessed in static setting, by utilizing randomly split data (García et al., 2015). It is important to be noticed that in reality the paths to default exhibit co-dependent and discontinuities events, and cannot be considered as a "Brownian random walk" (De Laurentis et al., 2010). The main advantage of generative AI in phase I is process automation and time acceleration. While one of the major concerns is possible data bias in the trained data. The algorithmic underwriting exceeds human underwriting process with 10.2 percent higher loan profits and 6.8 percent lower default rates (Morse, 2024). In phase I, proper forecasting of macroeconomic variables is essential. In Table 4 is presented the impact of 1 percentage point increase or decrease in the UK unemployment rate on Lloyds's portfolio assuming base case scenario.

Table 4 Unemployment rate impact on EL
Source: Lloyds Banking Group, 2024

	At 31 December 2023		At 31 December 2022	
	1pp increase in unemployment £m	1pp decrease in unemployment £m	1pp increase in unemployment £m	1pp decrease in unemployment £m
UK mortgages	33	(32)	26	(21)
Credit cards	38	(38)	41	(41)
Other Retail	19	(19)	25	(25)
Commercial Banking	88	(83)	100	(91)
ECL Impact	178	(172)	192	(178)

Further, Table 5 shows the UK mortgages increase/decrease impact on expected loss (EL) through loss given default in terms of 10 percentage point increase/decrease in the UK house price index (HPI).

Table 5 HPI impact on EL
Source: Lloyds Banking Group, 2024

	At 31 December 2023		At 31 December 2022	
	10pp increase in HPI £m	10pp decrease in HPI £m	10pp increase in HPI £m	10pp decrease in HPI £m
ECL Impact	(201)	305	(225)	370

In addition, the adoption of AI models by banks could allow them to collect and analyze digitally nontraditional data, including soft information in lending relation and support small businesses, which often do not have access to credit products, as this being vital for many countries. For example, micro, small, and medium enterprises (MSMEs) in Indonesia account for 99 percent of all enterprises in Indonesia, but comprise only 21.3 percent of all bank credit portfolio as of January 2022 (World Bank, IBRD, IDA, 2022). In addition, 54 percent of MSMEs struggle to obtain finance and Indonesia ranks fourth in the world in terms of unbanked population (World Bank, IBRD, IDA, 2022). Further, in Sub-Saharan Africa and Arab World only 9.81 and 9.87 percent of the retail clients borrowed from a formal financial institution in 2021 (presented in Figure 3 above). By utilizing AI credit models, financial institutions in these regions could serve those clients and boost their revenues.

Phase II

In general, banks use separate statistical models for to estimate retail portfolio's PD, EAD and LGD and corporate portfolio's PD, EAD and LGD (Maybank, 2023). There was a notable progress in the corporate portfolio's PD, EAD and LGD in the last few decades, starting from statistical models (Altman, 1968; Ohlson, 1980), moving to classical machine learning models (Fan & Palaniswami, 2000; Fedorova et al., 2013; Niklis et al., 2014) and expanding to deep learning models (Elhoseny et al., 2022; Hajek & Munk, 2024; Hosaka, 2019; Li et al., 2021; Mai et al., 2019; Wei at al., 2024). As per Lu et al. (2025) these models lack to understand and utilize the semantic behind the numerical values. One probable solution is the utilization of LLM (Korangi et al., 2023; Ruan et al., 2021; Wu et al., 2024). Recently, there is growing interest in utilization of textual data by researchers (Che et al., 2024; Choi et al., 2020; Hajek & Munk, 2024; Mai et al., 2019; Nguyen et al., 2021; Wang et al., 2023).

Broadly speaking, corporate clients are rated using a grade scale based on a Basel model utilized for an exposure (HSBC, 2024). Each band is linked with an external rating grade, related to long-run default rates by averaging issuer-weighted historical default rates for the respective grade (HSBC, 2024). On the other hand, the retail lending is entrenched to 12-month point-in-time probability-weighted PD (HSBC, 2024). For the PD estimation it is appropriate to be linked to a forward-looking economic guidance for the default rates specified for a particular industry in every country. While for LGD estimation, independent from the borrower's PD, a forward-looking economic guidance should be linked to collateral values and realization rates again related to a particular industry within a particular country. The impact of macroeconomic factors on the PD model, should be taken into account based on the outstanding maturity of the underlying assets. For LGD calculation for mortgage portfolios it should be incorporated forecasted loan-to-value estimates for the remaining maturity of the asset based on country level house price index forecasts while taking into account the expected future forecast collateral values. Deutsche Bank incorporates statistical models like logistic regression for to transform one-year PD to multi-year PD curve by utilizing through-the-cycle matrices and macroeconomic forecasts (Deutsche Bank, 2023). The process starts with transformation of through-the-cycle matrices into point-in-time rating migration matrices (in general for two-year forecast period), from which a multi-year PD curves are obtained (Deutsche Bank, 2023).

Further, in famous Merton model, a structural approach, default prediction is based on input values and laying out the insight into the default procedure. In comparison to agencies' ratings, Merton's model is more responsive to market activity, but at the same time it is more variable due to volatility in interest rates, market prices, etc. Structured models differ from reduced form models as the latter do not provide any ex-ante assumptions related to default drivers. Contrary, in reduced form models the default event is externally specified. The dependence of reduced form models on the sample data poses model risk (De Laurentis et al., 2010). Supervised learning, in which the neural network learn how to achieve a successful outcome on specified training set, is one of the most employed methods in the domain of credit risk.

There is an improvement in credit risk parameters with the use of ML methods (Hibbeln et al., 2023). ML applications are gaining popularity among financial institutions (Deutsche Bundesbank, 2020; Bank of England, 2019; Bank of Canada, 2018). They can change the landscape how the financial services are presented in the future (European Banking Authority, 2021). Multiple tree-based ML methods are found to befitting well for various credit risk parameters (Hibbeln et al., 2023). Model uncertainty can be overcome by the use of forecast ensembles (Hibbeln et al., 2023). Different forms of mixture models have been proposed for modeling highly skewed exposure at default (EAD) distribution (Betz et al. 2022; Thackham and Ma 2019; Hon and Bellotti 2016; Leow and Crook 2016). There is a greater use of ML models for loss given default (Kellner et al. 2022; Nazemi et al. 2022; Olson et al. 2021; Kaposty et al. 2020; Nazemi and Fabozzi 2018; Kalotay and Altman 2017; Altman and Kalotay 2014; Qi and Zhao 2011; Bastos 2010). A nonlinear relationship in a data is seen as an advantage for the advanced predictive abilities of ML models in different financial domains (Bali et al., 2023; Bianichi et al., 2021; Gu et al., 2020). EAD could be more accurately predicted by ML models (Hibbeln et al., 2023). As per some authors the time preceding default is related to increase usage of a credit line (Jiménez et al. 2009; Hibbeln et al. 2020). Collateral, seniority indicators and other security specific aspects report for more than one-fifth of the model recovery rate (RR) importance (Hibbeln et al., 2023). There is a positive correlation between smaller credit limits and credit conversion factor (CCF) prediction and negative correlation between larger credit lines and CCF prediction (Hibbeln et al., 2023). Small enterprises use more heavily credit lines as a source of financing (Chodorow-Reich et al. 2022). The RR is positively correlated with larger credit limits (Hibbeln et al., 2023). Larger undrawn values of CCF have positive correlation with RR prediction of CCF, while for the utilization rate of CCF the correlation is opposite (Hibbeln et al., 2023).

ML models have the ability to manage non-linearity in large credit datasets. On the other hand, due to their complexity there are some difficulties for their interpretation and analysis. Explainable AI tackles the “black box” problem linked to AI. An important attribute of explainability important for banks is the comprehension of the key features responsible for model’s prediction. Through the usage of explainable algorithm, banks can perceive each variable’s significance for the model’s prediction power. A lot of researchers found explainable AI (XAI) better suited for credit risk models, with SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) as the most suited ones (Misheva et al., 2021; and Nwafor & Nwafor, 2023). Gramegna & Guidici (2021) find that SHAP values possess superior discriminatory power in the ML models domain. Misheva et al. (2021) by utilizing SHAP and LIME on data from Lending Club for to describe ML-based output classifiers (XGBoost, logistic regression, support vector machine, and random forest) and one neural network classifier discover the superiority of SHAP over LIME. In general, SHAP framework bestow, for any machine learning model, local and global feature significance of value.

Further, utilizing LLM for feature extraction is gaining popularity especially bidirectional encoder representations from transformers (BERT), and an encoder-only model that utilizes bidirectional transformer encoders (Devlin et al., 2019). Stevenson et al. (2021) employ BERT with structured data for corporate default prediction. Further, many researchers utilize BERT and RoBERTa for credit default prediction based on user-generated texts (Kriebel & Stilz, 2022; Jiang et al., 2023; Kölbel et al., 2024; Wu et al., 2024). Yu et al. (2023) propose two stage framework, in which in the first phase through ChatGPT are obtained psychological personality traits from loan texts, and in the second phase through LightGBM is performed credit risk classification.

Phase III

Worldwide bank NPLs' figures in 2021 show some improvement in comparison to previous years (presented in Figure 7). The few countries with NPL ratios higher than 15 percent in the same year are mainly in Africa (Congo, Rep; Algeria, Ghana, Equatoria Guinea and Chad) (World Bank, DataBank, 2025). The peak of the NPLs in the observed period was in 2013 with countries mainly in Africa (Central African Republic, Djibouti, Equatorial Guinea) and East Europe (Albania, Bulgaria, Bosnia and Herzegovina, Croatia, Hungary, Montenegro) (World Bank, DataBank, 2025). San Marino is the country with the highest NPLs for the last three consecutive years (2019-2021) (World Bank, DataBank, 2025). Further, NPL ratios differ across regions, with Africa being the region with the highest NPLs, followed by Eastern Europe (presented in Figure 8).

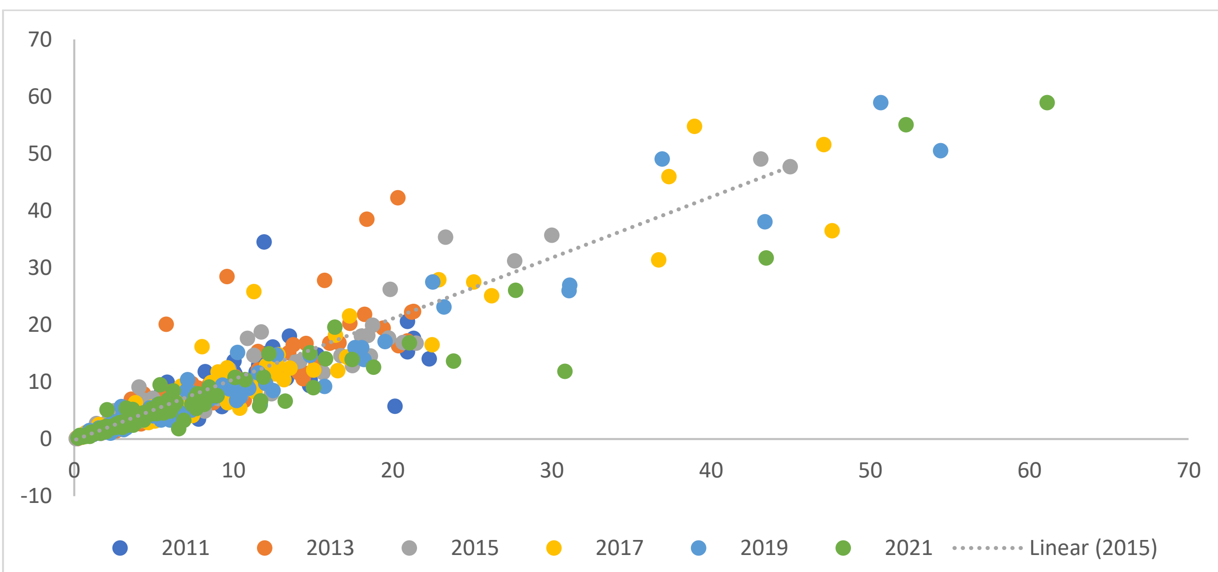

Figure 7 Worldwide bank non-performing loans to gross loans (%)
Source: World Bank, DataBank, 2025

In addition, NPL ratios worldwide show some trends:

- Increase in the NPL ratios during and after Global Financial Crises of 2008-2009
- During the period 2015 – 2018 there were considerable decrease in NPL levels (with exceptions as Africa and Middle East) mainly due to lower interest rates
- From 2019 to 2021 due to the COVID-19 pandemic there were spike in the NPL ratios but with heterogeneity in the magnitude or the time of the spike. As per some researchers NPL ratios during crisis exhibit similarities in the buildup, but they differ in the NPL resolution time (Ari et al., 2021).

In addition, emerging markets and developing economies are expected to suffer higher negative NPL dynamics during crisis in comparison to the advanced economies (Ari et al., 2021). Further, 30 percent of NPLs related to crisis, continue to carry on unresolved credits (Ari et al., 2021).

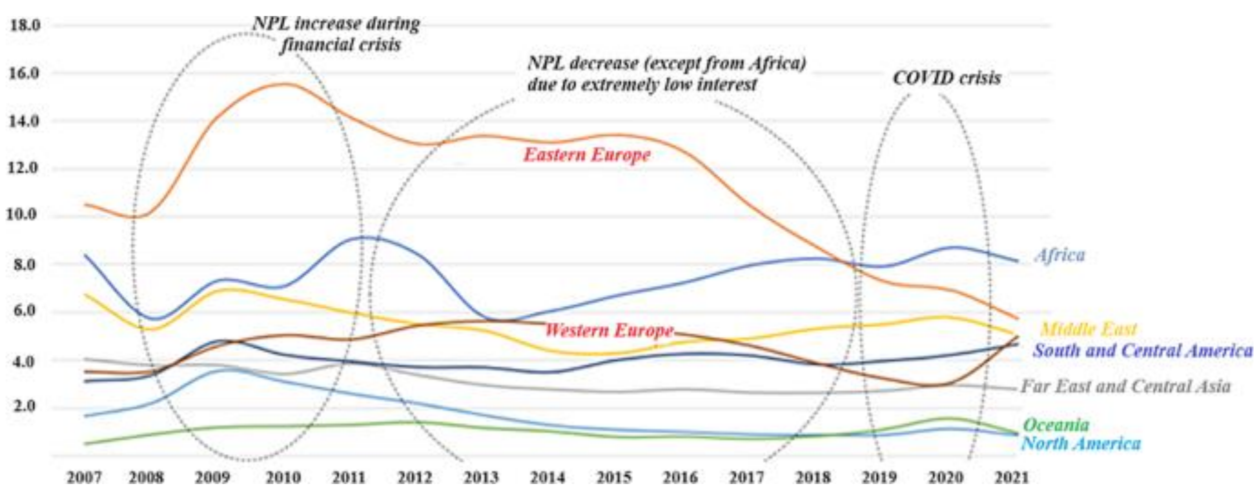

Figure 8 Impaired loans/ gross customer loans by region
Source: Salas et al., 2024

Loan recovery rates differ in terms of type of borrower, geographic area, and industry (as presented in Table 6). The lowest recovery rate in corporate portfolios is in Africa & Middle East and in service industry, while the lowest recovery rate in medium-sized portfolios is in Latin America and in social and health services (presented in Table 6). In terms of small-sized portfolios the lowest recovery rates are in Africa & Middle East and in services and wholesale/ retail trade (presented in Table 6). Africa & Middle East is the region with the lowest recovery rates in general, while Asia & Oceania is the region with the highest recovery rates (presented in Table 6). Agriculture is the industry with the highest recovery rates, while services is the industry with the lowest recovery rates (presented in Table 6). Medium-sized portfolios have the highest recovery rates, while small-sized portfolios have the lowest recovery rates (presented in Table 6). The above differences in the recovery rates in terms of portfolio size, region and industry should be incorporated in the models for better estimation on probability of default.

Table 6 Recovery Rate
Source: Global Credit Data, 2023

	Corporate			Medium-Sized			Small-Sized		
	Nr of Facilites	Observed Recovery Rate	Time to Peak Recovery	Nr of Facilites	Observed Recovery Rate	Time to Peak Recovery	Nr of Facilites	Observed Recovery Rate	Time to Peak Recovery
Africa&Middle East	4,418	67%	1.2	1,279	82%	1.6	2,534	58%	1
Asia&Oceania	8,628	80%	0.8	3,667	79%	0.8	2,981	86%	0.5
Europe	104,411	75%	1.4	52,218	81%	1.4	41,017	67%	1.5
Latin America	5,176	70%	1.5	1,933	68%	1.8	827	64%	1.3
North America	45,331	77%	1.2	26,741	81%	1.2	9,147	61%	1.2
Unknown	58	70%	1.4	7	57%	0.7	1	0%	
Agriculture	6,311	84%	1.2	4,508	86%	1.1	1,267	75%	1.1
Communicatons	4,130	73%	1.4	1,439	78%	1.5	1,168	63%	1.3
Constructon	16,657	75%	1.4	8,950	80%	1.4	6,284	67%	1.2
Hotels and Restaurants	6,407	74%	1.4	3,234	79%	1.5	2,557	66%	1.3
Manufacturing	32,931	78%	1.1	17,010	81%	1.1	8,567	70%	1.1
Mining	2,168	82%	1	742	81%	1.1	2,475	70%	1
Real Estate	14,821	82%	1.5	10,074	84%	1.5	2,742	75%	1.3
Social/Health Services	5,657	75%	1.7	3,823	76%	1.7	1,376	71%	1.9
Other Services	24,232	72%	1.3	11,238	79%	1.3	10,829	64%	1.3
Transportation	8,323	76%	1.1	3,310	81%	1.1	3,411	68%	1.2
Utilites	1,539	79%	1.2	554	82%	1.2	300	67%	1.1
Wholesale/Retail Trade	32,520	73%	1.2	15,736	79%	1.2	12,438	64%	1.2
Other	12,326	75%	2.1	5,227	81%	2	5,293	67%	2.5

Machine learning (ML) methods have been used in calculation of recovery rate, but mainly related to corporate loans, while there is some gap of models with focal point on retail credit products as credit cards and mortgages (Bellotti et al., 2019). Bellotti and Crook (2012) find that the inclusion of macroeconomic variables in the credit cards' recovery models have some positive impact on their forecasting capabilities, and indicators of housing market (Bellotti et al., 2019). For modeling retail loan recovery rates, the rule-based algorithms possess an important quality to isolate sub-group of clients (Bellotti et al., 2019). Random forests, boosted trees, cubist and other rule-based algorithms have the highest forecasting recovery rate (Bellotti et al., 2019).

Further, it is important to look into the NPL determinants. Seven out of ten most important NPL determinants are loan specific and three out of seven are borrower specific (presented in Figure 9).

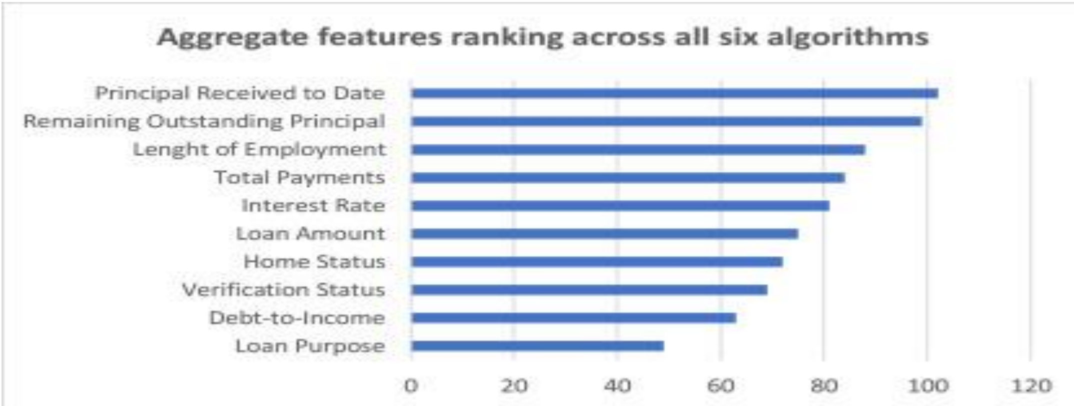

Figure 9 Ten most important NPL determinants
Source: Nwafor & Nwafor, 2023

In case of default, loss given default differs by region. Africa & Middle East and Latin America are the regions with the highest percentages of LGD (presented in Table 7). Latin America and Europe are the regions with the longest time to peak and recovery of LGD, as well for LGD resolution (presented in Table 7).

Table 7 Nominal loss given default by region
Source: Global Credit Data, 2025

Region	LGD	Time to peak & recovery	Time to resolution
Africa & Middle East	34%	1.2 years	2.1 years
Asia & Oceania	20%	0.8 years	1.2 years
Europe	26%	1.4 years	2.4 years
Latin America	32%	1.5 years	2.3 years
North America	23%	1.2 years	1.8 years
Other	34%	1.4 years	2.2 years

In addition, in terms of enterprise type, LGD has the highest percentage within small enterprises (presented in Table 8). Further, the highest peaks of LGD were during Global Financial Crisis, with another upward trend in 2020 (presented in Figure 10)

Table 8 Nominal loss given default by enterprise type
Source: Global Credit Data, 2025

Enterprise type	LGD
Small	33%
Medium	20%

Large	20%

As per some authors expected loss by itself does not embody a risk, but the variance of loss levels constitutes risk (Schroeck, 2002). Calculating expected loss (EL) based-on model assumptions and historical information may not be sufficient under more unpredicted future economic conditions (HSBC, 2024).

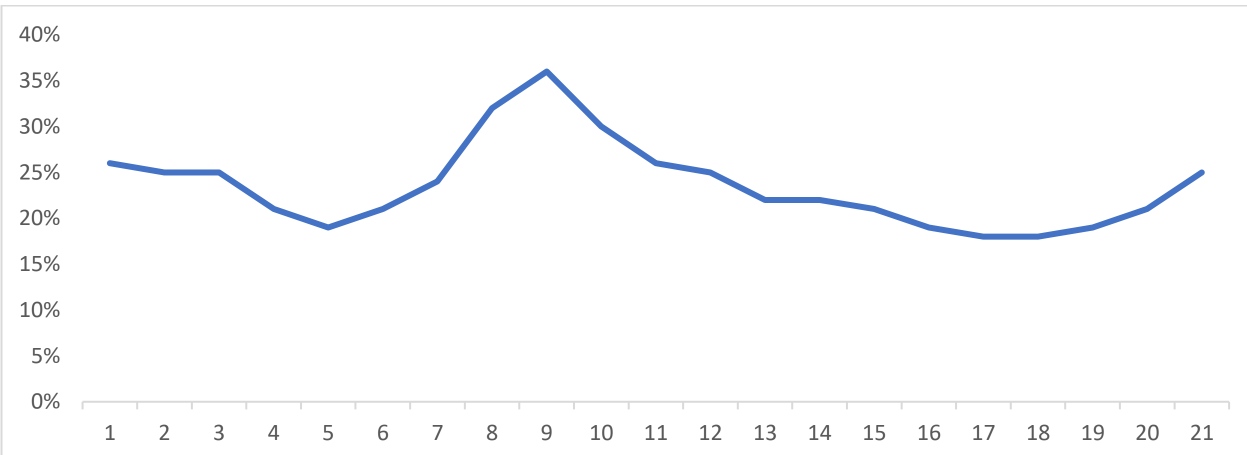

Figure 10 Discounted LGD from 2000 to 2020
Source: Global Credit Data, 2025

In general, there is some trade-off between customers' creditworthiness and their probability. In some cases, customers with higher probability of default could be more profitable for the bank, by utilizing more loan products even with higher interest rates, where comes the idea for "risk-based pricing". AI models can be utilized by banks for improving product's profitability and efficiency. Generative AI models could better analyze customer data for identifying specific segments and serving better customers' needs, and by providing new customer-center products enhancing customer experience.

IV. CONCLUSION AND RECOMMENDATIONS

The utilization of AI models in loan process by banks could improve their efficiency, reduce costs related to loan origination, speed the decision for loan recovery, increase bank competition and strength their operational efficiency. It could broadly have positive impact on the economy by improving the resource allocation, strengthening the resilience of financial institutions and deepening the financial sector. In the retail banking credit loan business, there is a huge protentional as only 28.38 percent of retail clients worldwide in 2021 borrowed from a formal financial institution (World Bank DataBank, 2024). And even more appealing to Sub-Saharan Africa and Arab World, where only 9.81 and 9.87 percent of retail clients borrowed from a formal financial institution for the same period (World Bank DataBank, 2024). The resource allocation by banks not only enhance the real economy, but also has many other crucial functions: liquidity provision, value exchange/ payment, etc.

There is an improvement in credit risk parameters with the use of ML methods (Hibbeln et al., 2023). They can change the landscape how the financial services are presented in the future (European Banking Authority, 2021). Multiple tree-based ML methods are found to befitting well for various credit risk parameters (Hibbeln et al., 2023). On the other hand, due to their complexity there are some difficulties for their interpretation and analysis. Explainable AI tackles the "black box" problem linked to AI. Generative AI models could better analyze customer data for identifying specific segments and serving better customers' needs, and by providing new customer-center products enhancing customer experience. This research could serve as a ground point for further empirical analysis.

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