

## عنوان

دور نمذجة مخاطر الائتمان في عمليات اتخاذ القرار بالمؤسسات المالية  
(SABB) في البنك السعودي البريطاني

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## **Abstract**

This study investigates the role and impact of credit risk modeling on decision-making at SABB (Saudi British Bank), evaluating its effectiveness and the challenges faced in its implementation. Credit risk modeling plays a critical role in financial decision-making, influencing loan approvals, risk assessment, and overall banking stability. The research employs a quantitative approach using a randomly selected sample of 282 respondents, gathered through an electronically distributed questionnaire. The findings highlight that SABB has successfully integrated advanced AI-driven technologies such as machine learning, big data analytics, and real-time credit risk assessment to enhance predictive accuracy and operational efficiency. Automated credit scoring significantly reduces approval times, while risk-based lending policies improve financial decision-making. However, challenges remain, particularly in model optimization, regulatory compliance, and employee training in AI-driven credit assessment tools. The study also identifies the importance of continuous updates to risk models, real-time data utilization, and structured validation processes to improve predictive accuracy and financial stability. While SABB has a well-structured risk assessment framework, further enhancements are needed in refining decision-making efficiency, reducing uncertainty, and ensuring a balance between profitability and risk mitigation.

Strengthening interdepartmental collaboration and investing in ongoing technological advancements are recommended to optimize credit risk modeling at SABB.

# **Chapter 1: Introduction**

## **1.1. Introduction**

Financial institutions need strong capabilities to handle risks properly because it determines both stability and profitability within their financial sector. Financial institutions face considerable risk through credit issues that occur when borrowers default on their debts leading to monetary damage. Sound financial strategy demands strong credit risk management practices since their implementation is now vital for ensuring stability and profitability. Credit risk modeling stands as the fundamental tool within these practices since it supports critical decision-making throughout banks and insurance companies and additional financial organizations (Bakurova et al., 2021).

Quantitative analysis techniques determine default probabilities of borrowers alongside assessing credit risk consequences on financial operations for institutions. Statistical as well as machine learning approaches are used through this modeling system that relies on historical datasets, A financial institution uses models that analyze both financial indicators alongside macroeconomic variables to create risk assessments which center around decision-making for loan approvals and interest rates and funding allocations. Management of financial institutions becomes more effective when they implement these models to use data in making decisions that optimize their

risk-return profiles and improve creditworthiness assessments. The company needs to adhere to regulatory requirements of Basel III standards in order to stay compliant (Doko et al., 2021).

Credit risk modeling acts as a fundamental element in financial institutions when they make decisions because it directly affects both strategic planning and policy creation. Financial institutions use accurate credit risk models to improve the management of their entire loan portfolio, Economic downturn analysis should lead companies to build sufficient capital reserves. This, in turn, supports the broader objectives of financial stability and resilience. Institutions can build predictive and extensive credit risk models with the help of improved technology and access to big data resources (Khalili & Khalilpour, 2016).

supports the broader objectives of financial stability and resilience. Institutions can build predictive and extensive credit risk models with the help of improved technology and access to big data resources (Khalili & Khalilpour, 2016). Knowledge of how credit risk modeling contributes to organizational decision-making enables understanding of financial institutions' risk management processes and their global market success mechanisms. This research delves into the strategic importance of credit risk modeling, The research examines how technology affects decision-making, supports regulatory requirements and modifies financial outcomes (Celayir & Benli, 2023).

## **1.2. Problem statement**

Credit risk management poses substantial hurdles to financial institutions which must navigate the trade-off between earning profits and controlling risk exposure because the risk nature evolves permanently. Credit risk modeling advancements have failed to stop financial institutions from obtaining precise models that track economic changes. Financial institutions encounter multiple significant hurdles when dealing with credit risk since the risk's constantly evolving state produces dilemmas between profit generation and

risk control levels. Financial institutions remain unable to produce accurate market prediction models for credit risk even though they achieved notable progress in credit risk modeling. Fast technological developments along with expanding big data availability demand continuous maintenance for credit risk models to maintain their predictive abilities according to Bakurova et al. (2021). The majority of institutions encounter implementation challenges between emerging approaches and innovative technologies yet these methods would boost their decision-making power. The prevention of complete loan assessment and pricing functions along with capital distribution occurs due to their limited decision-making capability. Financial organizations encounter significant obstacles while building credit risk models because those models must remain dependable and responsive to financial market fluctuations. The organization encounters weakened decision powers combined with money losses and additional regulatory hurdles which diminish its competitive advantages and ability to remain stable.

### **1.3. Research Significances**

#### **1.3.1. Theoretical Significance**

The study about Credit Risk Modelling in Financial Institutions' Decision-Making Processes brings important theoretical value to existing research on risk management and financial modeling. The review of underlying structures for credit risk models provides better understanding about their development process as well as their validation and field implementation. Financial theories related to risk assessment and probability of default benefit from additional value through this study, Modern assessments of creditworthiness can be achieved by applying contemporary understanding about how recent technology developments along with big data analytics work in the system. The study depicts all hurdles financial institutions encounter when trying to preserve both the accuracy and flexible nature of their credit risk assessment frameworks. The study demonstrates theoretical factors which will guide the construction of improved credit risk models that overcome present-day practice imperfections. The research facilitates both theoretical risk

management model refinement and supports academic discussions about risk modeling strategy improvements.

### **1.3.2. Practical Significance**

The results of this research offer important strategic value to financial institutions which need to optimize their credit risk management strategy and decision-making framework. Findings from this research will assist practitioners who need to create improved credit risk models that boost both credit assessment precision and enterprise-level financial planning. Financial institutions gain superior practices through improved risk mitigation and profitability by understanding the problems of poor quality data together with incomplete models and varying economic conditions. The study produces practical implications which help organizations fulfill their regulatory requirements, Institutions need their risk management approaches to follow global standards like Basel III. Stricter credit risk models enhance accurate capital management as well as financial reporting thus assisting institutions to stay compliant with regulations while preventing financial penalties. Financial professionals, The analyzing team can share their conclusions to policymakers and analysts who can use insights for developing modern analytical approaches and combining technological breakthroughs to build resilient credit risk management frameworks in evolving financial systems.

## **1.4. Research Objectives**

1. To investigate the role and impact of credit risk modeling in the decision-making processes at SABB (Saudi British Bank).

2. To evaluate the specific impact of credit risk modeling on the effectiveness of decision-making at SABB (Saudi British Bank).
3. To identify and analyze the challenges faced by SABB (Saudi British Bank) in implementing and maintaining effective credit risk models.

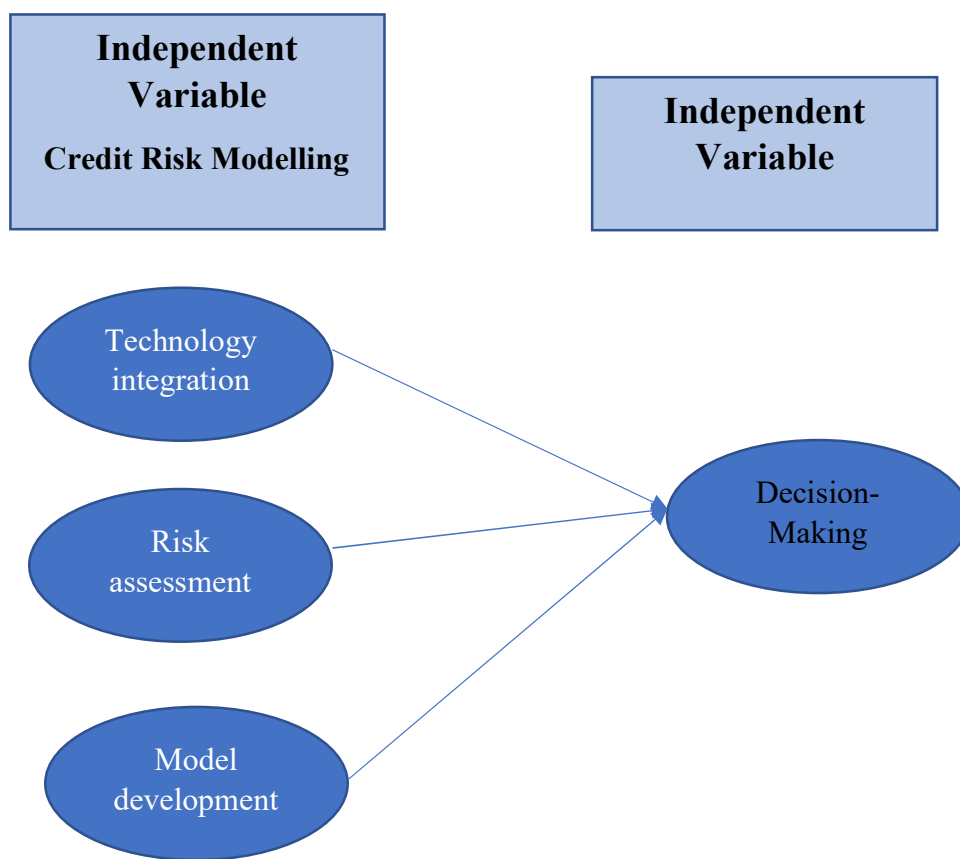
### **1.5. Research Questions**

1. What is the role and impact of credit risk modeling in the decision-making processes at SABB (Saudi British Bank)?
2. What is the impact of credit risk modeling in the decision-making processes at SABB (Saudi British Bank)?
3. what challenges does the bank face in implementing and maintaining these models effectively?

### **1.6. Research Hypotheses**

clear to us from the earlier figure, that the current research attempts to The Role of Credit Risk Modelling in Financial Institutions Decision-Making Processes at SABB (Saudi British Bank)

- ✓ Independent Variable :Credit Risk Modelling (Technology integration , Risk assessment, Model development)
- ✓ Dependent Variables: Decision-Making Processes



**Figure 1 Research Variables**

## 1.7. Study Limitations

1. Temporal Limitations: This study will be conducted over the course of 2024, ensuring that the data collection and analysis reflect current practices and challenges in credit risk modeling and decision-making processes at SABB (Saudi British Bank) within this specific time.
2. Spatial Limitations: The research will be confined to the operations and decision-making processes at SABB (Saudi British Bank).
3. Objective Limitations: The study aims to: comprehensively evaluate the current role of credit risk modeling in influencing decision-making processes at SABB, investigate the impact of credit risk models on decision outcomes related to risk management and financial strategy, identify and analyze the challenges SABB faces in implementing and maintaining effective credit risk models, and propose targeted strategies to enhance the use of credit risk modeling for improved decision-making. However, the research will not cover all possible variables that may impact decision-making or delve into unrelated aspects of financial operations that do not relate to credit risk modeling.
4. Human Limitations: The study will involve a targeted sample of employees at SABB, including credit analysts, risk managers, decision makers, and other relevant staff members. This research will gather essential information about credit risk model implementation in the bank through expert input from bank employees.

## **Chapter 2 :Literature review**

### **2.1. Introduction**

Effective decision-making in financial institutions relies heavily on credit risk modeling due to quick advancements in the financial sector today. Banks together with their lending branches function under conditions of continuous uncertainty which stem from market instabilities and regulatory developments and differences between loan applicants' conduct. Because of this ability to assess credit risks the likelihood that a borrower will default on their financial obligations—has become essential to protect institutions from instability and optimize loan portfolios and minimize financial losses. The sophisticated tool of credit risk modelling lets banks evaluate and predict credit risk in order to make knowledgeable financial decisions about lending investment and planning. Modern analytical models have fundamentally changed the manner through which SABB (Saudi British Bank) and other financial institutions process credit assessments while managing their portfolio risks. Pragma banks improve their credit evaluation system via statistical methods and artificial intelligence with big data analytics applications, The banking structure operates with greater security and profitability because of this model (Bluhm et al., 2016). This part examines how credit risk modeling serves financial decision-making processes to boost banking performance by decreasing default rates.

### **2.2. Literature review**

Wu & Hsu (2012) established a vital research initiative to evaluate credit risk assessments through their comprehensive decision-making approach for improved reliability in credit evaluation results. Published in Knowledge-Based Systems, This study pursued to enhance standard credit risk assessment techniques through different analysis solutions to build an

advanced creditworthiness evaluation framework. The authors noted how conventional model maintains common use particularly, The analytical tools struggle to understand credit risk complexities because they use static data together with restricted analytical methods. The researchers from Wu and Hsu developed a fusion method which integrates the capabilities of fuzzy logic with decision trees and support vector machines to address these research limitations. The integrated method provided improved interpretation of credit data which led financial institutions to make more precise and informed business decisions. New joint methods exceeded single approach methods in electing both more efficient predictions and lower miss-classification rate outcomes. The findings added to research by demonstrating how multiple analytical frameworks should be used in credit risk modeling. Financial institutions that want to enhance their credit evaluation processes should use this research because a combination of assessment methods produces superior decision results. The research by Wu and Hsu created a fundamental basis for researchers who later studied sophisticated integrated risk modeling approaches to handle modifying financial risk management needs.

Coolridges (2013) examined the innovative power of generative artificial intelligence (AI) through a research article published in *Emerging Trends in Machine Intelligence and Big Data* by Yusof & Roslan (2023). The research goal focused on examining how generative AI technology enhances credit risk model precision and operational efficiency for banking institutions to make improved decisions. Studying artificial intelligence systems to understand how they could eliminate existing weaknesses in conventional credit risk models because of sparse datasets and rigid system models was the main research goal. The authors merged quantitative research methods with expert interview procedures to create their study. Testing Generative Adversarial Networks (GANs) together with conventional credit risk models

happened through quantitative evaluation of generative AI algorithms utilizing banking institution data. We conducted interviews with risk management professionals to understand practical implementation aspects of using generative AI systems for credit risk assessment during the qualitative part. The study affirmed that using generative AI to generate synthetic data completed training data gaps which boosted credit risk model prediction accuracy levels. Generative AI technology produced precise risk assessments while decreasing the number of incorrect positive identifications which allowed banks better decision-making in their lending processes. Interviewed risk management professionals perceived generative AI as a tool to improve operational efficiency in decision-making processes, The article stressed the need to handle data security issues and model transparency problems while proclaiming the essential advantages of generative AI within banking. The study results showed that generative AI implementation in credit risk modeling produces enhanced model precision together with polished decision-making capabilities for banking institutions according to Yusof and Roslan. They called for regulatory structures yet insisted that these systems require ethical AI standards which should resolve explainability and privacy issues. The research introduces an optimistic view by prompting banks to use generative AI systems as part of their credit risk management practices while maintaining appropriate technological and implementation standards.

E. V. Orlova (2019) introduced the Mechanism and Model for Decision-Making in Credit Risk Management through research at the Fourth Workshop on Computer Modelling in Decision Making (CMDM 2019). The research investigates advanced analytical tools which must be used because credit risk assessment and management has become more complex. The main goal of this research by Orlova involves developing a systematic decision system which applies computer modeling approaches to enhance credit risk assessment dependability along with

accuracy. This proposed system employs different analytical and computational technologies to generate more precise default predictions. Financial institutions need such methods to base their lending decisions on accurate data. The model design incorporates both theoretical models along with applicable applications which provide simulation tools for risk scenario evaluations toward credit portfolio assessments. The system uses historical data analysis and projection of future trends through relevant financial and economic indicators in its simulations, The model introduces an entrepreneurial method for managing credit risks. This research study uses quantitative methods together with data-driven analyses as its methodology. The approach provides complete capabilities to develop simulations that assess credit risk with enhanced accuracy levels. Studies done by Orlova show that implementing computer-based decision-making improves credit risk assessment precision substantially. The combination of computer modeling tools with financial analysis strengthens business decision-making related to credit risk uncertainty. The research by Orlova shows that this system would greatly boost decision quality in credit risk management which helps institutions reduce losses and improve their credit portfolio performance. The analysis unveils essential combinatory interests between technology and financial analysis which achieve enhanced results as new research and application approaches materialize in financial risk management.

K. Brown and P. Moles (2014) authored "Credit Risk Management" to deliver an extensive study about fundamental credit risk practices and methods in financial institution control. Organizations should implement different effective approaches for identifying and assessing and minimizing their credit risks according to the authors. The text provides both theoretical lessons alongside practical instructions about credit risk management in financial markets making it an essential resource. The framework created by Brown and Moles describes

the complete credit risk management stages covering the discovery of risks as well as their evaluation and subsequent implementation of risk reduction methods. Various risk assessment strategies including credit scoring and risk rating systems and quantitative models receive detailed explanations from the authors. These risk assessment instruments enable businesses to predict borrower default cases while assessing total loan participant profiles to make smarter financial decisions. One significant component of the book addresses regulatory factors together with their effects on credit risk management practices. Risk management practices and financial institution decision-making processes are influenced by the Basel Accords which are explained by Brown and Moles. It is necessary to understand existing regulations because they guide the creation of efficient risk management plans that respect all requirements. The publication explores several risk reduction approaches through discussions about the management of collateral assets as well as portfolio expansion techniques together with credit derivative usage. Such risk mitigation systems protect institutions from losses through procedures that maintain financial stability. Throughout their book the authors demonstrate credit risk management principles in real-life financial scenarios through practical examples and case studies. The method brings theoretical knowledge into practical use by showing readers how credit risk management techniques are applied. The writing examines contemporary trends together with difficulties blocking the development of credit risk managers who operate in volatile economic environments and global financial turmoil and dynamic credit markets. The section of the publication demonstrates that adaptability and forward-thinking minds are essential elements to succeed in credit risk management. For high-performing credit risk management organizations the necessity exists for never-ending education as well as proactive planning to tackle emerging challenges.

The study by Montevechi et al. (2024) provides through review of modern machine learning applications applied to credit risk modeling in Advancing Credit Risk Modelling with Machine Learning: A Comprehensive Review of the State-of-the-Art. The paper appeared in Engineering Applications of Artificial Intelligence with its publication in December 2024, Machine learning stands as a transformative force which brings new capabilities for predicting risks related to credit evaluation and generates additional detailed evaluation insights. The review examines the benefits which machine learning algorithms deliver when applied instead of traditional statistical models, The approach delivers three significant advantages: precision improvement together with flexible operation and capacity to handle and analyze sophisticated information. The text explains different machine learning approaches along with their beneficial qualities and negative aspects among decision trees, support vector machines, neural networks and ensemble models. An analysis of these challenges presents itself in the paper alongside the problems experienced in model implementation through data quality issues and struggles with interpretability alongside regulatory compliance requirements. By offering a thorough synthesis of recent advancements and applications, this review serves as a valuable resource for practitioners and researchers aiming to understand and adopt machine learning techniques for more effective credit risk management.

This research by Montevechi A. A. and his colleagues de Carvalho Miranda R. and Medeiros A. L. alongside Montevechi J. A. B. appeared in Engineering Applications of Artificial Intelligence (2024), This paper delivers an extensive review which explains machine learning integration into credit risk modeling in depth. The authors try to bridge traditional credit risk methods with contemporary advancements through their research on current machine learning practices and studies. The extensive review showcases the revolutionary effect machine learning

provides to credit risk evaluation. The use of machine learning algorithms provides numerous advantages beyond traditional statistical methods including accurate results and efficient operation of handling vast complicated data quantities. The paper describes different machine learning methods for credit risk modeling which include decision trees, support vector machines and neural networks alongside ensemble models while analyzing their benefits and competitive features. The authors draw attention to these methods as their primary focus, The usage of such systems presents increased accuracy in predictive modeling that improves financial decision-making in credit risk evaluation. The analysis identifies various challenges together with limitations which arise when using machine learning approaches to manage credit risks. The analysis focuses on the issue of data quality, Reliable data alongside data relevance together with model interpretability lead to effective model performance in the industry. Financial institutions face substantial regulatory challenges to demonstrate transparency in their models because they must obtain regulatory approval with their decision explanations. The authors emphasize that machine learning maintains its solution potential when obstacles are properly approached through planning and the implementation of hybrid predictive models which unite interpretability with high predictive capability. Montevechi and colleagues determine that using machine learning enhances credit risk models in financial technology by surpassing current traditional methods of risk assessment. The study urges further research and development activities, The entire credit risk analysis potential of machine learning requires both financial experts and data scientists to collaborate in order to resolve current challenges. The review provides essential knowledge to both researchers and practitioners who need to understand credit risk modeling practices and the challenges of using machine learning in their field.

A. Alrabiah (2018) in *Cogent Economics & Finance* investigates advanced credit risk management optimization in banking systems through a unified processing framework that unifies the entire business operations across banking (Optimal Regulation of Banking System's Advanced Credit Risk Management by Unified Computational Representation of Business Processes Across the Entire Banking System). The study underlines that banks must use a single approach to depict organizational processes because this creates stronger regulatory compliance and risk management capabilities. Alrabiah describes the difficulties of conventional credit risk management systems that combine fragmented operations with independent procedures which prevent superior choice-making and regulatory fulfillment. The research model implements a single computational format to create a unified view of business processes which improves departmental coordination and increases operational transparency in banking institutions. Advanced credit risk management becomes possible through an integrated approach which streamlines data flow according to the research findings, Risk assessment becomes more precise while potential credit risks get identified at appropriate times through this approach. The model assists organizations in uniting their credit risk management strategies while it enables consistent data interpretation and regulatory reporting needs. Furthermore The research demonstrates how banks would use this single model to handle regulatory changes better alongside market changes which results in better business resiliency and flexibility. System installation requires technical infrastructure evaluation in combination with organizational readiness studies so financial regulators can work with their technical staff according to Alrabiah. The paper delivers essential knowledge regarding the use of unified computations for business process representation which optimizes financial risk management and regulatory processes in banking systems. This approach promotes a comprehensive, The system creates an integrated perspective which improves risk management approaches and fulfills

regulatory standards and enhances financial institution stability. Theoretical foundations of the study.

## **2.3. Theoretical foundations of the study.**

### **2.3.1. The Importance of Credit Risk Modelling in Financial Decision-Making**

The long-term success along with sustainability of financial institutions depends on their skill to approach and control various risks properly. Among all risks which affect banks Credit Risk stands as the most vital because it impacts directly on a bank's financial state and both its cash flow capabilities and its future revenue potential. A carefully constructed credit risk model creates standardized procedures for financial institutions to determine potential borrower risk highest levels so they can base their lending decisions on data-driven methods.

#### **1. Enhancing the Accuracy of Credit Assessments**

Through credit risk modeling organizations check the probability of default using historical information together with borrower details plus economic trends data. Financial institutions use complex algorithms to distinguish risky borrowers from the lower risk population thereby minimizing defaults from people who will not repay their debts (Löeffler & Posch, 2011). Through machine learning analysis these technological models find relationships and patterns in extensive data collection that normal scoring systems would pass by. Through these evaluations banks can use advanced information to extend their risk evaluation approach past traditional credit scoring systems.

#### **2. Improving Strategic Decision-Making**

A well-developed credit risk model enables financial institutions to obtain enhanced insights about their risk profile. Banks must have this vital information when they determine loan policies together with interest rates and credit restrictions. The precise assessment of potential

defaults helps banks choose better capital deployment locations that will produce lasting earnings. Through credit risk models financial institutions get the capability to modify their risk tolerance according to present market situations. When economy faces downturns banks typically tighten their lending criteria yet in periods when the economy is stable they expand their loan activities for market growth.

### **3. Compliance with Regulatory Requirements**

Financial institutions operate under strict regulatory frameworks, such as Basel III and local regulations enforced by institutions like the Saudi Arabian Monetary Authority (SAMA). These regulations require banks to maintain adequate capital reserves based on their risk exposure, ensuring financial stability (Bielecki & Rutkowski, 2013). Advanced credit risk models help banks comply with these regulations by providing accurate risk assessments, allowing them to determine the appropriate capital reserves needed to cover potential losses. Without effective credit risk models, financial institutions may struggle to meet regulatory requirements, resulting in penalties, reputational damage, or operational inefficiencies.

### **4. Supporting Sustainable Banking Growth**

By integrating credit risk modelling into their decision-making processes, banks can create a more resilient financial system. Proper risk assessment ensures that banks avoid excessive risk-taking, which could lead to major financial crises, such as the 2008 global financial crisis, which was largely caused by poor credit risk assessment and excessive lending (Duffie & Singleton, 2012). Furthermore, by adopting AI-driven credit risk models, banks can extend their reach to underbanked populations who may not have traditional credit histories but demonstrate strong repayment potential based on alternative data sources, such as transaction histories, utility payments, and online financial behavior.

### **2.3.2. Its Role in Improving Banking Performance and Reducing Default Rates**

The ability to minimize loan defaults while maintaining a profitable lending portfolio is a key objective for any financial institution. Credit risk modelling plays an essential role in achieving this goal by allowing banks to proactively identify, measure, and manage risk factors before they result in financial losses.

#### **1. Reducing Non-Performing Loans (NPLs)**

One of the primary challenges faced by banks is the accumulation of non-performing loans (NPLs) loans that borrowers are unable to repay. High NPL ratios can severely impact a bank's liquidity, profitability, and investor confidence. By utilizing predictive credit risk models, financial institutions can detect early warning signs of borrower distress, enabling them to take initiative-taking measures, such as restructuring loans, adjusting credit terms, or increasing reserves for potential losses (Bluhm et al., 2016). For example, many banks use behavioral scoring models that track changes in borrower financial behavior, such as overdue payments or irregular account activity, to anticipate defaults before they occur. This allows banks to take preemptive action, reducing the overall rate of default.

#### **2. Enhancing Loan Portfolio Performance**

A well-balanced loan portfolio is crucial for the financial health of any bank. Credit risk models help institutions optimize their loan portfolios by diversifying their exposure across different sectors, industries, and customer segments. For instance, banks can adjust their risk exposure by dynamically modifying their credit allocation strategies based on the evolving economic environment. If a particular sector is facing economic downturns (e.g., real estate or oil and gas), banks can reallocate lending resources to more stable industries, reducing overall risk (Bielecki & Rutkowski, 2013). Moreover, risk-based pricing models allow banks to adjust interest

rates based on borrower risk profiles, ensuring that higher-risk borrowers are charged appropriately while rewarding lower-risk customers with competitive rates.

### **3. Improving Customer Experience and Loan Approval Efficiency**

Traditional credit evaluation processes can be time-consuming and bureaucratic, leading to delayed loan approvals and lost business opportunities. Modern AI-powered credit risk models significantly speed up loan processing times by automating risk assessments, enabling banks to approve loans faster without compromising risk management standards. For example, in digital banking, credit risk models allow for instant loan approvals based on real-time risk assessments, enhancing customer satisfaction and engagement. Faster decision-making not only benefits customers but also reduces operational costs for banks, making the lending process more efficient and scalable.

### **4. Strengthening Risk Mitigation Strategies**

A well-structured credit risk model enables banks to develop effective risk mitigation strategies, including:

Credit insurance to protect against borrower defaults.

Loan restructuring programs to assist distressed borrowers and minimize losses (Khandani et al., 2010).

Advanced AI systems work with big data analysis to detect fraudulent activities.

The application of risk mitigation strategies allows banks to operate at sustainable profit margins throughout high-risk decisions and maintain lower financial risk levels. Financial institutions depend heavily on credit risk modeling to achieve risk-management goals through proper business profitability achievement. The utilization of credit risk models enhances banking performance by improving accuracy in decision-making and decreasing non-performing loans and maximizing

loan portfolios while enhancing customer experience and enhancing risk management strategies (He & Xiong, 2012). For SABB (Saudi British Bank), Split Advisory still uses advanced credit risk models based on AI and big data which creates potential benefits for both operational effectiveness and regulatory requirements and market performance. The financial technology evolution will shape banking sector risk management through the combination of big data analysis with blockchain and artificial intelligence in credit risk models. Credit risk modeling in banking will adopt three key innovations including big data analytics, blockchain and artificial intelligence to establish how the sector should manage risks in the future.

### **2.3.3. Credit Risk**

When borrowers fail to fulfill their financial obligations lenders experience financial damages. This situation is known as credit risk. Multiple models exist to measure and reduce credit risk because their development began with statistical methods while now advanced methods based on artificial intelligence (AI) and machine learning (ML) serve the same purpose. The application of these models leads financial institutions to make better decisions which help them determine borrower creditworthiness and minimize risk while conforming to regulations (Agarwal & Mazumder, 2013). The section analyzes conventional credit risk models which define financial choice making processes, The research proceeds with a description of contemporary AI techniques which are revolutionizing credit risk evaluation practices. Traditional credit risk models served as fundamental tools to establish mathematical systems which evaluate loan default possibilities. These analytical systems utilize both historic accounting data together with mathematical measurements to operate, The analysis of both financial statements allows for creditworthiness evaluations. Among the prominent traditional models stands Merton's Model together with Altman's Z-Score while classical statistical models complete this list.

## **1. Merton's Model (1974) – Structural Credit Risk Model**

The Merton's Model represents the first theoretical framework addressing credit risk evaluation since it establishes a method to measure default probabilities for firms. Option pricing theory serves as the foundation for the model which developers created in 1974. In Merton's model companies use equity as a call option instrument for their assets. Merton's Model is founded on the premise that default happens when debt maturity reveals an asset value less than existing liabilities (Khandani et al., 2010). The model demonstrates how financial market information enables risk assessment of credit situations through asset volatility and value determination. Stochastic evolution defines a central part of Merton's Model because it demonstrates that a firm's asset values will experience random fluctuations from market dynamics throughout time. A default threshold exists in the model under which firms default when their asset values fall beneath defined boundaries matching debt obligations (Samra, 2016). The model depends on the Black-Scholes option pricing framework to calculate probabilities by determining when firm assets drop beneath their debt obligations until maturity. The practical use of Merton's Model encounters multiple restrictions which limit its effectiveness in raw credit risk assessment scenarios. The model contains a significant deficiency because it makes the restrictive assumption of market efficiency. This principle states that asset prices mirror all accessible information but real-world conditions do not necessarily validate this assumption. The model faces hurdles when trying to value assets precisely because market-based data is hard to obtain from private companies (Klapper & Lusardi, 2020). The model contains simplified representations of firm actions and bankruptcy procedures that might not faithfully represent actual default scenario complexities. The theoretical ground for present-day risk modeling approaches derives from Merton's Model even though it faces various implementation obstacles. KMV Moody's Credit Monitor takes the theoretical framework to

advance the approach through market-based credit risk indicators along with empirical adjustments to improve accuracy. The original limitations apply to this model yet it functions as a basic tool which guides financial researchers and risk managers in their work.

## **2. Altman's Z-Score Model (1968) – Predicting Corporate Bankruptcy**

Through financial ratio analysis the Altman Z-Score Model acts as the preferred statistical tool to identify bankruptcy potential in organizations. The linear discriminant analysis method uses discriminant analysis (LDA) to categorize business entities under three categories from financially sound to bankrupt condition based on their financial state. Statistical credit risk assessment at financial institutions depends on LR and LDA models within their procedures for evaluating credit risk. Borrower data from the past drives the scoring process that utilises scorecards to estimate default risk first by scoring various financial metrics ranging from credit history to payment behavior and income data. Discriminant analysis classification provides lenders a method to divide borrowers between low-risk and high-risk profiles which aids their decision-making processes. Data distribution that follows the normal curve and linear relationships form the main drawbacks of statistical models when analyzing financial data in its natural non-linear patterns. Traditional statistical risk assessment models encounter two major operational issues in extracting important connection patterns and undisclosed borrower behavioral patterns (Krimminger & Nieto, 2015) while current AI-based risk scoring solutions perform better with evolving financial databases. Traditional credit risk operational boundaries provided the foundation to build current-day credit risk methodologies therefore filling essential preexisting gaps. Modern credit risk assessment models emerged from combining big data analytics and artificial intelligence to generate pronounced risk predictions that actively monitor credit assessment in real-time. The new models match the changing financial market dynamics.

### **2.3.4. Modern Approaches to Credit Risk Modelling**

The combination of technology and machine learning and big data analytics gave credit risk modeling new capabilities that allow systems to overcome static financial ratio systems and linear prediction models. Modern financial conditions receive improved predictions and financial

adaptability through real-time data processing alongside pattern recognition algorithms and self-learning models. AI for credit risk assessment through its implementation enables models to find complex information patterns in large data collections which standard detection methods cannot discover. The predictive capabilities of neural networks become stronger through identifying non-linear relationships between borrower characteristics (Al Lawati et al., 2021). The combination of NLP technologies within AI systems enables them to process multiple forms of alternative data ranging from social media patterns to market indicators and transaction records that produce superior risk evaluation outcomes..

ML models function as effective credit risk tools which provide data-based analysis superior to conventional statistical methods. The supervised ML models use past credit data to train themselves for identifying borrowers who belong to high-risk and low-risk categories. Unsupervised ML models help financial institutions detect upcoming risks because they can identify hidden risk clusters present in their loan portfolios. Reinforcement learning algorithms maintain dynamic capabilities to adjust to market changes in real time because they work better in volatile financial markets according to Agarwal & Mazumder (2013). Random Forest and Decision Trees serve among the leading advanced ML approaches for credit risk modeling and display high potential in non-linear risk assessment. The performance of Gradient Boosting Machines (GBMs) surpasses basic regression models through better predictive outcomes and Support Vector Machines (SVMs) achieves superior risk classification precision. Modern technology enables better models in credit risk assessment by enhancing precision levels and system flexibility thus facilitating better lending decisions for banks across changing financial markets.

### **2.3.5. Importance of Credit Risk Modelling**

The constantly changing financial world has established credit risk modelling as an essential instrument for institutions to judge and reduce lending connected risks. Credit risk prediction together with analysis and management ability helps banks make strategic financial choices by improving their loans and

reducing losses. The rising complexity of global markets and regulatory framework along with borrower uncertainties drives SABB (Saudi British Bank) to use advanced credit risk modeling systems which help them face economic changes and regulatory decisions. The third part analyzes credit risk modeling by examining its three primary roles including improving credit decision reliability and upholding regulatory requirements and enhancing bank market leadership.

### **2.3.6. Greater accuracy in giving credit decisions arises from improved prediction of default probabilities**

#### **➤ The Need for Accurate Credit Risk Assessment**

Institutions relying on financial operations need precise borrower default assessments for achieving financial stability during their risk-heavy operations. Standard credit scoring techniques along with manual underwriting processes from traditional times failed to identify all risk indicators so banks experienced higher default rates along with non-performing loans (Al Lawati et al., 2021). Evaluation methods which use data analytics alongside artificial intelligence software and statistical models now enable more precise prediction of default probabilities in credit risk assessments. Using these risk models examines historical financial information as well as market and borrower data and economic influences to produce detailed risk assessments for applicants.

#### **➤ How Credit Risk Modelling Improves Decision Accuracy**

##### **1. More Precise Borrower Evaluation:**

- Credit risk models quantify default probabilities based on credit history, income levels, debt obligations, and behavioral data.
- AI-powered models go beyond traditional credit scoring by analyzing real-time transaction data, digital footprints, and alternative credit indicators (Kumar & Goyal, 2015).

##### **2. Early Detection of High-Risk Borrowers:**

- Predictive models identify patterns of financial distress before they escalate into defaults.
- Banks can implement proactive risk mitigation strategies, such as loan restructuring or adjusting interest rates based on borrower risk profiles (Sarker, 2021).

### **3. Reduction in Non-Performing Loans (NPLs):**

- With improved risk prediction, banks can minimize exposure to high-risk loans, reducing the percentage of NPLs in their portfolios (Kavun & Vorotintsev, 2016).
- A lower NPL ratio leads to better asset quality, improved liquidity, and stronger financial performance.

#### **2.3.7. Regulatory Compliance: Alignment with Basel III and SAMA Regulations**

Financial institutions need regulatory compliance as they establish a stable risk-controlled environment for their credit risk management practices. The strict guidelines set by Basel III and Saudi Arabian Monetary Authority (SAMA) protect against excessive risk-taking and financial instability because they were established after the 2008 global financial crisis caused by improper risk assessment and careless lending (Weber, 2012). The Bank for International Settlements (BIS) developed the Basel III Accord which requires banks to hold additional capital reserves while using strict risk assessment tools to test the financial stress impact on operations (Mwangi, 2012). The compliance requirements of Basel III demand contemporary credit risk models along with the accuracy of Probability of Default (PD) and Loss Given Default (LGD) and Exposure at Default (EAD) estimates to promote sufficient capital reserves and better liquidity risk management capabilities through predictive analytics (Butaru et al., 2016). The Saudi Monetary Authority applies stringent regulations to credit risk management which demands banking institutions to establish detailed credit evaluation procedures along with IFRS 9 ECL provisions and scheduled credit portfolio stress tests. The growing requirement for regulatory compliance leads financial institutions to implement AI-based credit risk models which execute automated risk evaluations

together with error reduction systems to provide real-time stress testing capacity for banks to maintain effective reporting protocols (De Wet, 2010). Banks achieve financial safety and investor trust through regulatory-compliant credit risk modeling of their framework which leads them to operate securely within a sustainable banking system.

### **2.3.8. The improvement of banking competitiveness depends on minimizing risks and achieving maximum profitability**

Modern banking institutions require sophisticated risk management techniques to maintain profitability and limit possible financial losses during their competition in today's market. The implementation of credit risk models offers financial institutions essential tools for strategic performance since it facilitates loss reduction and grouping of customers efficiently and uses automated systems for risk assessment (Bluhm et al., 2016). Sophisticated risk evaluation models allow banks to conduct data-driven lending decisions that give loans to qualified borrowers while preventing high-risk applicant exposure. The core benefit of credit risk modelling for profitability enhancement occurs when organizations optimize their loan portfolios. Banks use accurate PD and risk factor predictions to establish economic lending plans that profitably target borrowers with better assurance of paying back their debts. The combination allows financial institutions to achieve reliable earnings and minimal non-performing loans (NPLs) which protect profitability.

Sustained loan approval operations represent another major advantage of this system. The process of traditional lending depends on staff conducting lengthy credit evaluations that often produce incorrect results. The implementation of AI-based risk models permits banks to perform automated credit evaluation which speeds up both the loan process and preserves exactness. The improved operational processes alongside better customer experience and prompt decision-making support banks to maintain their position as market leaders in current banking systems. Financial institutions use credit risk modeling to achieve market leadership through new approaches and

ideas. Financial institutions which implement machine learning along with big data analytics and creative credit score assessment can produce personalized lending methods for every customer segment. Financial institutions utilize advanced analytics along with real-time data to offer personalized loan products and dynamic interest rates and adjustable credit solutions thereby creating competition between them and their rivals. Banks leverage predictive risk analytics to modify their operations while staying competitive in the market which ultimately builds both profitability and stronghold in their market sector.

### **2.3.9 Challenges in Credit Risk Modelling**

The advancements of credit risk modeling technology in financial decision processes and risk evaluations do not eliminate the difficulties which companies must address. SABB (Saudi British Bank along with other financial institutions operates through a diverse array of technical and financial and regulatory challenges during their implementation and maintenance of strong credit risk modeling systems. Modern financial institutions maintain difficulties with their data capabilities alongside expensive implementation costs as well as strict regulatory mandates even with current machine learning technologies and big data and artificial intelligence capabilities. The assessment accuracy and operational efficiency suffer from such challenges which negatively impact profitability and compliance standards (Baesens et al., 2016). The subsequent part identifies main difficulties facing credit risk modeling by analyzing data problems alongside funding restrictions and mandatory regulatory obligations.

#### **1. Data Challenges: Issues Related to Data Quality and Privacy**

##### **✓ The Role of Data in Credit Risk Modelling**

Data serves as the foundation of any credit risk model, influencing the accuracy and effectiveness of risk assessment. The ability of financial institutions to predict borrower default risk relies heavily on the quality, completeness, and accuracy of available data. Poor data quality can result in flawed risk predictions, leading to the misclassification of high-risk borrowers as creditworthy

or the rejection of low-risk applicants who could be valuable customers. Ensuring that credit risk models are trained on reliable, diverse, and well-integrated data sources is essential for improving their predictive capabilities and reducing financial risk.

#### ✓ **Common Data-Related Challenges**

One of the most prevalent data-related challenges in credit risk modelling is incomplete and inconsistent data. Many borrowers, especially in developing markets, lack formal credit histories, making it difficult to assess their risk profile. Small businesses and startups often operate without structured financial statements, which complicates the evaluation of their creditworthiness (Chatterjee et al., 2011). Additionally, inconsistent borrower records, missing data points, and outdated information can lead to biased risk models that fail to provide accurate credit risk predictions. Another significant issue is data privacy and security concerns. Regulatory bodies enforce strict data protection laws, such as the General Data Protection Regulation (GDPR) and Saudi Arabian Monetary Authority (SAMA) guidelines, which restrict access to sensitive customer financial information. While these regulations aim to protect consumer privacy, they also pose challenges for banks and financial institutions, limiting their ability to collect and analyze comprehensive credit risk data. Moreover, financial institutions must ensure that their credit risk models do not violate privacy rights by improperly using or storing personal financial data (Bluhm et al., 2016).

A third challenge arises from data silos and integration issues, where many banks still rely on legacy systems that are incompatible with modern AI-driven risk models. Integrating structured data sources, such as financial statements and credit bureau reports, with unstructured data sources, including social media activity and behavioral data, remains a major hurdle (Bluhm et al., 2016). Additionally, the lack of standardized data-sharing practices among financial institutions, credit

bureaus, and regulatory agencies creates inconsistencies in credit risk assessments, making it difficult to develop accurate, real-time predictive models.

### ✓ **Addressing Data Challenges**

Financial institutions face data-related impediments which they overcome by using alternative credit risk assessment methods from new data sources. Banks can create an extensive financial profile about their borrowers by accessing data from telecom providers together with utility payments and e-com transactions. AI-driven behavioral analysis enables evaluative risk assessment for people without standard credit documentation by following a modern approach founded on data-based methods. The resolution of credit risk modeling inefficiencies mainly requires better management of data governance procedures. The adoption of cloud-based data management solutions by banks facilitates better data accessibility as well as integration while improved security features (Löeffler & Posch, 2011). Financial institutions can access proven borrower data through blockchain technology and achieve data transparency and prevent fraud to ensure they use verified evidence that is tamper-proof.

Data-driven credit risk modelling requires regulatory compliance to be its main priority. Banks need to strike the right balance between data acquisition procedures and privacy security of customer information while making sure their risk evaluation models follow ethical principles of artificial intelligence and local privacy laws. Secure machine learning models can achieve accurate predictions while satisfying regulatory requirements which leads to trust establishment between customers and regulators for sustainable financial operations.

### ✓ **Impact on SABB**

Saudi British Bank (SABB) should concentrate on handling its data-related challenges because this will enable better credit risk modeling and stronger lending choices with improved customer service outcomes. SABB can decrease default risks and provide extended credit opportunities to vulnerable markets and achieve superior industry position through alternative data implementation linked with predictive AI

analytics in conjunction with SAMA regulatory compliance. SABB's success in managing data challenges will result in offering customized loans and operational improvements and stronger long-term customer connections and a well-functioning credit risk system that adheres to all regulations.

### **2.3.10 High Costs: Investment in Technology and Infrastructure**

The deployment of sophisticated credit risk models results in substantial financial expenses for banks within the financial institution sector. Funding innovative technology infrastructure development represents the main expense alongside staffing specialized personnel and maintaining regulatory standards during AI-based credit risk evaluation. Operational expenses rise from the requirements to develop and sustain these models because they need high-performance computing abilities and cloud-based analytics solutions together with real-time data processing frameworks. Additional financial strain occurs because Basel III and IFRS 9 create capital requirements and demand annual stress tests and frequent audit procedures. Banks need permanent investment in AI model operation employee training since this process leads to both expensive recruitment costs and essential workforce upskilling programs.

Every financial institution needs to deal with numerous complicated regulations from international bodies and domestic jurisdictions to meet their compliance requirements. Financial institutions need to follow Basel III and IFRS 9 standards by developing risk-weighted capital buffers and performing assessments under stressful conditions and reporting results exactly according to strict guidelines. Institutions operating in Saudi Arabia need to follow specific guidelines from the Saudi Arabian Monetary Authority (SAMA) which mandates intense risk monitoring and complete transparency practices. The implementation of AI-based credit risk models produces ethical difficulties including biased decision systems and data protection matters that need increased regulatory oversight. Banks ensure compliance through frequent internal audits and stress testing and through strategic investments in advanced compliance technologies as well as the development of

transparent AI models which both regulators and stakeholders can analyze. The established measures support risk reduction while increasing the level of trustworthiness.

### **2.3.11 Case Study: Credit Risk Modelling at SABB**

The necessity of regulatory compliance plays a fundamental role in data-based credit risk modeling processes. Banks need to strike a proper equilibrium between gathering consumer data and protecting privacy rights to build risk assessment systems that match ethical criteria and local data protection legislation. Members of data security teams alongside regulatory authorities gain trust from customers when they implement secure AI models which meet all compliance standards thus supporting long-term ethical financial operations.

#### **✓ Impact on SABB**

Saudi British Bank (SABB) should concentrate on handling its data-related challenges because this will enable better credit risk modeling and stronger lending choices with improved customer service outcomes. SABB can decrease default risks and provide extended credit opportunities to vulnerable markets and achieve superior industry position through alternative data implementation linked with predictive AI analytics in conjunction with SAMA regulatory compliance. SABB's success in managing data challenges will result in offering customized loans and operational improvements and stronger long-term customer connections and a well-functioning credit risk system that adheres to all regulations.

### **Improving Loan Approval Processes and Reducing Non-Performing Loans**

Traditional loan approval processes were manual, time-consuming, and susceptible to human error, leading to delays, increased administrative costs, and a poor customer experience. Inefficient risk assessments also contributed to higher non-performing loans (NPLs), negatively affecting financial stability (Bluhm et al., 2016). To address these challenges, SABB implemented AI-driven automation and real-time credit risk analytics, significantly enhancing loan approval workflows. AI-based credit scoring systems now process applications within seconds, reducing

approval times from weeks to minutes. Risk-adjusted lending policies ensure that low-risk applicants receive near-instant approval, while high-risk cases undergo deeper evaluation. Additionally, AI models minimize human bias by replacing subjective underwriter judgment with consistent, data-driven risk assessments (Addo et al., 2018). Furthermore, dynamic risk-based pricing models allow AI to adjust interest rates based on borrower risk levels, ensuring favorable loan terms for low-risk applicants while imposing stricter conditions on high-risk borrowers. This approach optimizes loan profitability while reducing default probabilities (Löeffler & Posch, 2011), ultimately improving financial stability and operational efficiency.

### **2.3.12 High Costs: Investment in Technology and Infrastructure**

The deployment of sophisticated credit risk models results in substantial financial expenses for banks within the financial institution sector. Funding innovative technology infrastructure development represents the main expense alongside staffing specialized personnel and maintaining regulatory standards during AI-based credit risk evaluation. Operational expenses rise due to the necessity of high-performance computing and cloud analytics tools with data analysis capabilities that run in real time for developing maintaining credit risk modeling systems. Additional financial strain occurs because Basel III and IFRS 9 create capital requirements and demand annual stress tests and frequent audit procedures. Banks need permanent investment in AI model operation employee training since this process leads to both expensive recruitment costs and essential workforce upskilling programs.

Every financial institution needs to deal with numerous complicated regulations from international bodies and domestic jurisdictions to meet their compliance requirements. The Basel III framework along with IFRS 9 promotes financial institutions to create capital reserve levels according to risk-weighted measures yet they must perform stress tests while respecting strict reporting requirements. Institutions operating in Saudi Arabia need to follow specific guidelines from the Saudi Arabian Monetary Authority (SAMA) which mandates intense risk monitoring and complete transparency practices. The implementation of AI-based credit risk models leads to ethical risks because decisions can show bias and create privacy concerns

thus requiring more supervision. Banks need to achieve compliance by performing periodic internal audits and stress tests and by adopting advanced compliance technologies as well as creating AI models which stakeholders and regulators can accurately inspect. The established measures support risk reduction while increasing the level of trustworthiness.

### **1. Natural Language Processing (NLP) for Alternative Risk Indicators**

As a part of its analytics SABB uses artificial intelligence to examine financial media reports and official statements that detect market and business-based risks through sentiment measurement. The NLP system evaluates customer opinions and identifies warning indications of financial problems through complaint patterns so that the bank can implement precautionary steps for preventing credit default. An amalgamation of AI technologies provides SABB superior capabilities to make default predictions and real-time risk analysis while allowing access to alternative data sources for complete credit assessment.

### **2. Benefits of AI and Predictive Risk Modelling at SABB**

The employment of AI models enables improved PD forecasting which helps diminish borrower misidentification errors.

- ✓ Machine learning applications enable SABB to detect both dubious financial transactions and credit application scams.
- ✓ The automated system provides instant loan approvals to low-risk borrowers by decreasing lending processes.

**1.** SABB established its position as innovative leader in risk management through AI-based predictive risk models which increased loans transparency and cut down financial losses.**Outdated**

### **Technological Infrastructure:**

Traditional banking systems often rely on legacy infrastructures that do not align with the requirements of modern models. This misalignment leads to difficulties in data integration and system communication. Upgrading these systems is often costly and demands significant

investment in modern technology, along with the necessary training for technical staff to manage the new updates (Zhao et al., 2013).

## **2. Data Quality and Integration:**

High-quality, well-integrated data is crucial for the success of credit risk evaluation models. In many traditional systems, data is fragmented or heterogeneous, scattered across different databases. This fragmentation hinders comprehensive analysis. Additionally, the lack of standardized protocols for data collection and storage makes it challenging to transform raw data into a format suitable for advanced analytical models.

## **3. The Gap Between Quantitative Analysis and Traditional Operations:**

Modern risk evaluation models leverage quantitative analysis, artificial intelligence, and machine learning techniques. In contrast, traditional banking systems often depend on qualitative assessments and historical experiences in decision-making. This disparity creates a challenge in merging the two approaches, as it necessitates restructuring administrative processes and modifying credit policies to accommodate the new methodologies (Khan et al., 2015).

## **4. Regulatory and Supervisory Challenges:**

Regulatory bodies impose stringent standards on financial institutions concerning risk management and transparency in credit evaluation. Updating traditional systems to support modern models poses a regulatory challenge, especially when local and international laws and regulations may not be fully compatible with technological innovations. Additionally, the integration process requires updating internal policies and restructuring some procedures to comply with new supervisory requirements.

## **5. Resistance to Cultural and Organizational Change:**

Institutional culture plays a critical role in adopting new technologies. Many banks may encounter resistance from employees who are accustomed to traditional risk evaluation methods. Organizational change requires time and concerted efforts from top management to ensure that all personnel embrace the necessary changes, thereby facilitating the integration of new and traditional systems (Dionne, 2013).

## **6. Cybersecurity and Data Protection:**

Integrating modern systems with traditional ones introduces additional challenges related to cybersecurity. The establishment of new communication channels between different systems increases the risk of cyberattacks. This risk necessitates the implementation of stringent security measures to protect sensitive data and ensure the overall safety of the integrated systems.

### **2.3.13 Ethical Considerations and Transparency in Credit Risk Models**

Attention to ethical concerns stands as an important factor during credit risk model development because their absence produces damaging effects on particular customers while intensifying societal inequalities. Here are the primary elements which demonstrate why these aspects should be important:

- **Identifying and Addressing Implicit Bias:**

.credit models depend on past information but this historical data previously included biases because of banking activities or societal influences. Analysis of both data and algorithms represents a vital step for detecting and resolving any bias which could result in biased unfair treatment of customers (Bluhm et al., 2016).

- **Transparency and Accountability:**

The process of trust-building for credit decisions requires complete transparency about operational model mechanisms which both customers and regulatory bodies should understand easily. The supply of policy procedures and standard practices applied during model development and a detailed outcome explanation provides necessary accountability measures.

- **Regular Review and Ethical Evaluation:**

Examinations should happen sporadically to check how the models interact ethically with different demographic groups. Such reviews enable model developers to modify and update systems by following legal and social advancements thus protecting various groups from detrimental impacts.

- **Compliance with Legal and Ethical Standards:**

Every model system needs to follow both local and international laws and ethics in operation. The implementation of adherence requirements helps enhance customer right protection while minimizing the likelihood of discrimination issues and unequal banking service distribution. Through their emphasis on ethical considerations financial institutions develop a fair credit system which achieves economic effectiveness while maintaining social responsibility (Bielecki & Rutkowski, 2013).

## **2.3.14 Future Trends in Credit Risk Modelling**

### **1. The Role of AI in Credit Risk Modelling**

Traditional risk assessment methods have transformed through artificial intelligence since it allows real-time analysis while making automated decisions using programs that evolve their performance with each use. AI-based credit risk models help financial organizations make more precise high-risk borrower detections while speeding up the loan assessment process and catching fraudulent financial applications through behavioral pattern analysis (He & Xiong, 2012).

- Through automated decision systems the organization can decrease loan processing durations.
- The system detects fraudulent credit applications through behavioral pattern assessment (He & Xiong, 2012).

Finance institutions use AI models including neural networks along with decision trees and reinforcement learning to evaluate clients past real-time financial transactions in addition to digital profile information and behavioral psychology signals.

### **The Impact of Big Data on Credit Risk Assessment**

- The vast databases accessible by banks through big data allows them to develop enhanced credit risk assessments using:
- The analysis of banking transactions helps institutions measure individual spending habits together with their financial position.
- Social media platforms enable verification of borrower trustworthiness by analyzing their posted content according to Agarwal and Mazumder (2013).
- The assessment of individuals without established credit history relies on alternative financial activities including online shopping and utility payments.

Big data analytics allows AI models to recognize delicate patterns of borrower conduct which results in improved risk evaluation procedures compared to standard financial criteria

### **2.3.15 Leveraging AI and Big Data for Risk Analysis**

#### **2. The Role of AI in Credit Risk Modelling**

Traditional risk assessment methods have transformed through artificial intelligence since it allows real-time analysis while making automated decisions using programs that evolve their performance with each use. AI-based credit risk models help financial organizations make more precise high-risk borrower detections while speeding up the loan assessment process and catching fraudulent financial applications through behavioral pattern analysis (He & Xiong, 2012).

- Through automated decision systems the organization can decrease loan processing durations.
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- Finance institutions use AI models including neural networks along with decision trees and reinforcement learning to evaluate clients past real-time financial transactions in addition to digital profile information and behavioral psychology signals.

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- The assessment of individuals without established credit history relies on alternative financial activities including online shopping and utility payments.

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### **2.3.16 Blockchain Technology and Smart Contracts for Transparency**

#### **✓ The Need for Transparency in Credit Risk Modelling**

Through smart contracts blockchain technology finds its main use in risk management for credit by enabling digital agreements that automatically execute on distributed ledger systems. The implementation of smart contracts through blockchain technology enables automatic loan release and repayment tracking and risk surveillance that eliminate human staff and eliminate manual procedures. Smart contracts embedded with predefined loan provisions help financial institutions conduct automatic credit agreement execution to achieve better operational performance and limited dispute probability. Automation of smart contracts leads to direct loan disbursement while reducing expenses due to eliminated third parties. The credit process takes longer when banks collaborate with credit bureaus and legal teams and regulatory bodies because administrative expenses rise and approval duration extends. Fast reliable and cost-effective financial lending transactions become possible through the application of smart contracts by financial institutions. Smart contracts provide financial institutions with the ability to build permanent credit records that help minimize both deceptive accounting and financial fraud. Blockchain technology permanently stores data in

a way that protects all recorded information from unauthorized changes and therefore builds stronger relationships between financial borrowers and lenders.

#### ✓ **Benefits of Blockchain in Credit Risk Assessment**

Blockchain technology delivers multiple benefits to credit risk evaluation and its most substantial advantage enables improved data integrity. A distributed ledger system within blockchain architecture allows secure real-time storage and verification and updates of all credit-related information. The system prevents unauthorized changes in credit information while reducing potential errors for risk assessment processes that lead to increased accuracy and visibility in assessments. The main benefit of blockchain technology involves immediate and effective processing of loan approvals. Standard lending practices along with loan distribution require extensive weeks or days while underwriters and compliance officers perform their reviews manually. Blockchain technology enables financial institutions to perform automatic loan application procedures that lead to swift processing of borrower data verification and automatic agreement executions by smart contracts. The time-saving speed benefits especially those who run small businesses or operate as individuals since they need quick access to cash while waiting through the lengthy government-controlled lending process.

#### ✓ **Challenges of Blockchain Adoption in Credit Risk Modelling**

Various barriers impede blockchain's adoption as a solution for credit risk modelling before it can be fully implemented across industries. Financial regulatory bodies need to address regulatory uncertainty by writing guidelines for blockchain-based credit assessments because numerous regulators still lack established standards. The current banking regulations struggle to cooperate with the principles of decentralized financial technologies which forces lending institutions to deal with difficulties when implementing blockchain into their credit risk systems while maintaining regulatory compliance.

The oldest issue banks face is incorporating blockchain systems into existing traditional financial infrastructure. The IT infrastructure that typical financial institutions use does not function properly with blockchain network protocols. Establishing a credit risk system based on blockchain technology demands

significant spending on new technologies and cybersecurity solutions combined with employee training programs. The integration between blockchain and established risk analysis systems will lead to operational problems when banks experience difficulty combining them. Blockchain transactions face scalability problems because they currently operate at speeds below what is needed for extensive credit risk assessment (Klapper & Lusardi, 2020). Today's financial sector executes millions of transactions per day which demands blockchain networks to operate their bank service operations such as credit assessments and repayments in real time at high speed. The adoption of blockchain platforms for main credit risk modeling purposes remains restricted by their current limitations in scalability.

#### ✓ **The Future of Blockchain in Credit Risk Management**

While blockchain technology remains in development for the credit risk sector it provides essential features of transparency and security and automation potential which indicates it will dominate financial risk assessment developments in the future. Financial institutions plan to adopt decentralized credit risk systems through improved scalability and regulatory developing infrastructure which will boost their accuracy in lending and fraud protection and operational productivity. The banking sector can achieve a safer and inclusive financial ecosystem through regulatory challenge solutions and blockchain system scale-up investments alongside smart contract implementation and deployment.

#### **2.3.17 Model Risk Management and Validation**

The accurate functionality of credit risk evaluation models depends on model risk management and validation which remains unattended in previous sections. The necessity to perform routine reviews of risk evaluation models emerges from economic shifts and customer behavior modification because these assessments should confirm model forecasting accuracy and capacity for responding to new market conditions.

The element consists of several vital aspects which include:

- **Regular Review and Continuous Evaluation:**

The models must undergo testing with current dataset information to evaluate actual outcomes which will help detect weaknesses so issues can be resolved quickly. The operational framework supports model accuracy enhancement and improves predictive power as time progresses according to Krimminger & Nieto (2015).

- Identification and Management of Model Risks:

Model reliability depends on specific assumptions which become less accurate with changing circumstances so regulatory guidelines need to control model-related risks. The regulatory framework must include detection systems that identify model performance failures because it provides procedures to trigger correct courses of action that prevent continued usage of deficient models.

- Independent Oversight and Governance:

The performance of models requires independent monitoring teams who perform audits both internally and externally to evaluate the effectiveness of these models. The oversight system ensures both transparency in addition to compliance with worldwide and local regulatory requirements that builds trust in the credit risk results stemming from these models.

- Integration with Comprehensive Risk Management Strategies:

The inclusion of model risk management within Enterprise Risk Management (ERM) structures enables organizations to better handle emerging financial environment changes together with potential risks. The pairing of model risk management with ERM strategies brings better credit assessment results and reduces vulnerabilities that develop when monitoring existing models negligently (Kumar & Goyal, 2015). The fundamental aspect for improving credit risk evaluation model credibility involves implementing model risk management and ongoing model effectiveness validation thus guaranteeing dependable analytics for informed decision-making and risk minimization.

## **Chapter 3: The methodology**

### **3.1. Introduction**

The methodology of the study will be presented, including a description of the sample, the research tools used, and the method of their preparation. This section will also detail the validity and reliability of the tools. Furthermore, it will clarify the statistical methods and treatments employed, which were primarily used to analyze the study's hypotheses, aiming to achieve reliable scientific results.

### 3.2. Research Approach

This study was conducted to answer the questions raised, and therefore, it relied on a quantitative approach to examine the Role of Digital Marketing in Shaping Consumer Behavior in the E-commerce Industry **During this study, the researcher relied on two types of data:**

- **Primary Data:** This was collected through a field study where a data collection tool, namely a questionnaire designed by the researcher, was used. The questionnaire was distributed to the study sample, and the data collected was analyzed using the Statistical Package for the Social Sciences (SPSS) to reach scientific results.
- **Secondary Data:** This includes reliable scientific information gathered from academic books, research papers, and studies related to the study topic, as well as published research articles relevant to the study variables.

### 3.3. Research Design

#### 3.3.1. Research Sample

A random sampling method was employed to select the study sample. The questionnaire was distributed electronically through social networking sites to gather responses. The study sample comprised (282) The table below presents the characteristics of the sample.

Table 1 Characteristics of the Research Sample

| Characteristics     | Sub Characteristics | N          | %           |
|---------------------|---------------------|------------|-------------|
| Gender              | Female              | 143        | 50.7        |
|                     | Male                | 139        | 49.3        |
| Age Group           | 18 - 29 Years old   | 62         | 22.1        |
|                     | 30 – 40 years old.  | 100        | 35.4        |
|                     | 41- 50 years old.   | 47         | 16.8        |
|                     | 51 – 59 Years old   | 47         | 16.5        |
|                     | 60 or more years    | 26         | 9.1         |
| Educational Level   | High School         | 24         | 8.5         |
|                     | Bachelor's degree   | 181        | 64.3        |
|                     | Master's degree     | 71         | 25.1        |
|                     | Doctorate degree    | 6          | 2.1         |
| Years of experience | Less than 5 years   | 79         | 28          |
|                     | From 6 to 10 years  | 75         | 26.6        |
|                     | From 11 to 15 years | 35         | 12.5        |
|                     | 16 or more years.   | 92         | 32.6        |
| Total               |                     | <b>282</b> | <b>100%</b> |

### 3.3.2. Data Collection

The study tool consisted of a questionnaire divided into two sections as follows:

- **Section One:** This section gathered basic demographic data of the sample members, including educational qualifications, years of experience, job position, and age.
- **Section Two:** This section included the core items of the questionnaire, comprising 32 items divided into two principal areas:
  - ✓ **Axis One: Credit Risk Modelling:** This area is further divided into three dimensions:
    - First dimension of Technology Integration consistent with form 5 items
    - ✓ The second dimension of Risk Assessments consistent with form 5 items
    - ✓ The third dimension of Technology Factors is consistent with form 5 items
    - ✓ The four dimension of Model Developments consistent with form 5 items

The questionnaire will be used in order to collect data through the five-point Likert scale, which can be expressed through the following table:

Table 2 The Five- Point Likert Scale

| Term          | Strongly<br>Disagree | Disagree | Neutral | Agree | Strongly<br>Agree |
|---------------|----------------------|----------|---------|-------|-------------------|
| Answer Degree | 1                    | 2        | 3       | 4     | 5                 |

### 3.3.3. The Validity

Internal consistency was used to measure the validity of the tool by assessing the extent to which each item of the questionnaire is consistent with its corresponding construct. Pearson correlation coefficient was used to measure the correlation between each item and the total score of the construct it belongs to, as shown in the following table:

Table 3 The results of the correlation coefficient for the validity of the tool

| Pattern Scales         |                     |                |                   |                     |                |                   |                     |                |                           |                     |                |
|------------------------|---------------------|----------------|-------------------|---------------------|----------------|-------------------|---------------------|----------------|---------------------------|---------------------|----------------|
| Technology Integration |                     |                | . Risk Assessment |                     |                | Model Development |                     |                | Decision-Making Processes |                     |                |
| No                     | Pearson Correlation | Sig.(2 Tailed) | No                | Pearson Correlation | Sig.(2 Tailed) | No                | Pearson Correlation | Sig.(2 Tailed) | No                        | Pearson Correlation | Sig.(2 Tailed) |
| 1                      | 0.732               | 0.000          | 1                 | 0.871               | 0.000          | 1                 | 0.780               | 0.000          | 1                         | 0.95                | 0.000          |
| 2                      | 0.713               | 0.000          | 2                 | 0.880               | 0.000          | 2                 | 0.782               | 0.000          | 2                         | 0.871               | 0.000          |
| 3                      | 0.760               | 0.000          | 3                 | 0.889               | 0.000          | 3                 | 0.790               | 0.000          | 3                         | 0.885               | 0.000          |
| 4                      | 0.760               | 0.000          | 4                 | 0.908               | 0.000          | 4                 | 0.707               | 0.000          | 4                         | 0.871               | 0.000          |
| 5                      | 0.715               | 0.000          |                   | 0.824               | 0.000          | 5                 | 0.802               | 0.000          | 5                         | 0.877               | 0.000          |

Through this table, it is evident that all items have correlation coefficients within a certain range 0.504: 0.838 and all were significant at a significance level of 0.000 .This indicates that the questionnaire has an elevated level of reliability.

### 3.3.4. The Reliability

Table 4 The results of Cronbach's alpha coefficient for the reliability of the tool.

| Variables | Number | Axis Stability |
|-----------|--------|----------------|
|-----------|--------|----------------|

|                           |                        |    |       |
|---------------------------|------------------------|----|-------|
| Decision-Making Processes | Technology integration | 5  | 0.890 |
|                           | Risk assessment        | 5  | 0.702 |
|                           | Model development      | 5  | 0.770 |
| Decision-Making Processes |                        | 5  | 0.830 |
| Total Cronbach's Alpha    |                        | 20 | 5.028 |

To calculate the questionnaire's reliability, we used Cronbach's alpha coefficient to determine the tool's stability. The following table shows the reliability coefficients. The table indicates that the questionnaire has an elevated level of reliability, with Cronbach's alpha values for the questionnaire's axes ranging from to. This demonstrates that the scale has an elevated level of stability, meaning the results are consistent each time the scale is applied. Therefore, this questionnaire can be reliably used to generalize the results.

### **3.3.5. Study Procedures**

Initially, the questionnaire was designed by reviewing previous studies related to the research topic and the collected theoretical frameworks. After designing the questionnaire, it was presented to several experts for review, and necessary amendments were made through deletion and addition. Next, the validity and reliability of the tool were assessed. The questionnaire was then prepared electronically and distributed via social networking sites such as Facebook and WhatsApp. After the survey was administered, data were collected to achieve reliable scientific results.

### **3.3.6. The Statistical Method**

The data collected from the sample were entered using the program (SPSS-V.22). The statistical methods that were used to process the data varied, including:

- Cronbach's Alpha coefficient to ensure consistent performance.
- Use frequencies and percentages to determine the significance of the sample's responses to the questionnaire items.
- Correlation coefficient for the calculation of honesty.
- Regression analysis

## **Chapter 4: Analysis and Results**

### **4.1. Introduction**

This chapter details the statistical analysis of the collected data, outlining the analytical processes used to derive clear and meaningful scientific information. These processes are designed to achieve the study's objectives and address its research questions.

## 4.2. Statistical Analysis and Results Interpretation

### 4.2.1. Axis One: Credit Risk Modelling

- **First Dimension: Technology Integration**

Table 5 The result of Technology Integration

| No    | Items                                                                                                            | Mean  | SD    | Order | The reliability |
|-------|------------------------------------------------------------------------------------------------------------------|-------|-------|-------|-----------------|
| 1     | The bank effectively integrates advanced technologies (AI, big data analytics) to enhance credit risk modelling. | 3.85  | 0.799 | 1     | -               |
| 2     | Automated credit risk models have improved the accuracy of risk predictions.                                     | 3.63  | 1.069 | 3     | -               |
| 3     | The integration of technology in credit risk modelling has reduced manual errors and improved efficiency.        | 3.85  | 0.881 | 2     | -               |
| 4     | The bank continuously updates its credit risk modelling tools to keep up with industry trends.                   | 3.62  | 0.976 | 4     | -               |
| 5     | Employees are well-trained in using technology-driven credit risk assessment tools.                              | 3.56  | 1.061 | 5     | -               |
| Total |                                                                                                                  | 18.51 | 4.786 |       | 0.890           |

The findings presented in Table 5 highlight the effectiveness of technology integration in credit risk modelling at SABB (Saudi British Bank). The results indicate that the bank has successfully implemented advanced technologies such as AI and big data analytics to enhance its credit risk assessment processes. The highest-rated statement, "The bank effectively integrates advanced technologies to enhance credit risk modelling" (Mean = 3.85, SD = 0.799), suggests that technology adoption is a strong aspect of the bank's risk management framework. This underscores the importance of leveraging AI-driven predictive analytics to improve credit risk evaluation and decision-making. Additionally, the statement "The integration of technology in credit risk modelling has reduced manual errors and improved efficiency" (Mean = 3.85, SD = 0.881) ranks second, reinforcing the idea that automation and digital tools have minimized human errors and enhanced operational efficiency. This aligns with global trends in the financial sector, where machine learning and AI-driven models are being widely used to improve risk accuracy and reduce errors in credit evaluations. However, some areas show room for improvement. The statement "Automated credit risk models have improved the accuracy of risk predictions" (Mean = 3.63, SD = 1.069) ranks third, indicating that while technology enhances predictive accuracy, there may still be challenges related to model optimization, data quality, or regulatory compliance. Similarly, "The bank continuously updates its credit risk modelling tools to keep up with industry trends" (Mean = 3.62, SD = 0.976) suggests that while updates occur, they may not be fully optimized or implemented consistently across all risk assessment processes. The lowest-rated item, "Employees are well-trained in using technology-driven credit risk assessment tools" (Mean = 3.56, SD = 1.061), suggests a potential gap in employee training and digital literacy. This implies that while technology is being integrated, more efforts may be needed to enhance employee expertise, provide continuous training programs, and ensure that all staff members can effectively utilize

digital credit risk assessment tools. The total mean score (18.51) and reliability coefficient (0.890) indicate strong internal consistency in responses, confirming that technology integration plays a significant role in improving credit risk modelling at the bank. However, the findings suggest that continuous updates, employee training, and further improvements in predictive accuracy should be prioritized to maximize the benefits of digital transformation in credit risk management.

- **Third Dimension: Risk Assessment**

Table 6 The results of Risk Assessment

| No    | Items                                                                                 | Mean  | SD    | Order | The reliability |
|-------|---------------------------------------------------------------------------------------|-------|-------|-------|-----------------|
| 1     | The bank has a well-structured credit risk assessment framework.                      | 3.63  | 1.024 | 4     | -               |
| 2     | Risk assessment models accurately identify high-risk clients before approving credit. | 3.65  | 0.976 | 3     | -               |
| 3     | The credit risk assessment process is regularly reviewed and improved.                | 3.60  | 1.087 | 5     | -               |
| 4     | The bank uses real-time data to assess credit risk effectively.                       | 3.81  | 1.024 | 1     | -               |
| 5     | Risk assessment results are reliable and contribute to minimizing financial losses.   | 3.65  | 1.176 | 2     | -               |
| Total |                                                                                       | 18.34 | 5.287 |       | 0.770           |

The findings in Table 7 provide insights into the effectiveness of risk assessment as part of the credit risk modelling framework at SABB (Saudi British Bank). The results indicate that the bank has a structured approach to evaluating credit risk, but there are areas where improvements can be made to enhance accuracy and efficiency. The highest-rated statement, "The bank uses real-time data to assess credit risk effectively" (Mean = 3.81, SD = 1.024), suggests that the bank places a strong emphasis on leveraging real-time financial and customer data for risk evaluation. This is a crucial aspect of modern credit risk management, as real-time data analytics allows for quicker decision-making and better identification of potential defaulters. The second-highest rating was given to "Risk assessment results are reliable and contribute to minimizing financial losses" (Mean = 3.65, SD = 1.176), indicating that while the bank's risk models are effective in mitigating financial risks, there may still be areas for improvement in predictive accuracy or loss prevention strategies. The statement "Risk assessment models accurately identify high-risk clients before approving credit" (Mean = 3.65, SD = 0.976) ranked third, showing that the bank's risk assessment models are generally effective in distinguishing high-risk clients. However, a slightly lower mean score suggests possible limitations in model precision, data completeness, or predictive power. Meanwhile, "The bank has a well-structured credit risk assessment framework" (Mean = 3.63, SD = 1.024) ranked fourth, implying that while a structured framework exists, further refinements may be needed to align with industry best practices and evolving regulatory requirements. The lowest-rated statement, "The credit risk assessment process is regularly reviewed and improved" (Mean = 3.60, SD = 1.087), highlights an area for potential enhancement. Although the bank has a review system in place, there may be a need for more frequent updates, enhanced validation methods, or more advanced review mechanisms to keep up with changing risk patterns. The total mean score (18.34) and reliability coefficient (0.770) indicate moderate internal consistency, confirming that

the risk assessment dimension is a crucial factor in the bank's credit risk modelling process. However, to strengthen the effectiveness of risk assessment, further investment in real-time data analytics, continuous model improvements, and more rigorous review cycles is recommended. This would ensure that the bank remains proactive in identifying risks, minimizing financial losses, and improving credit decision-making accuracy.

- **Four Dimension: Model Development**

Table 7 The results of Model Development

| No | Items                                                                                                    | Mean | SD    | Order | The reliability |
|----|----------------------------------------------------------------------------------------------------------|------|-------|-------|-----------------|
| 1  | The bank continuously develops and refines credit risk models to improve decision-making.                | 3.82 | 0.866 | 3     | -               |
| 2  | Credit risk models are tailored to meet the specific needs of different client segments.                 | 3.76 | 0.929 | 4     | -               |
| 3  | There is a structured process for validating and testing new credit risk models.                         | 3.93 | 0.843 | 1     | -               |
| 4  | The credit risk model development team collaborates with other departments for data-driven improvements. | 3.75 | 0.931 | 5     | -               |

|       |                                                                                              |       |       |   |       |
|-------|----------------------------------------------------------------------------------------------|-------|-------|---|-------|
| 5     | The bank ensures compliance with regulatory requirements when developing credit risk models. | 3.89  | 0.838 | 2 | -     |
| Total |                                                                                              | 19.15 | 4.407 |   | 0.923 |

The findings in Table 8 provide insights into the model development process for credit risk assessment at SABB (Saudi British Bank). The results indicate that the bank has a well-structured approach to developing, testing, and refining credit risk models, ensuring that decision-making processes are data-driven and aligned with regulatory requirements. The highest-rated item, "There is a structured process for validating and testing new credit risk models" (Mean = 3.93, SD = 0.843), highlights that the bank prioritizes the validation and continuous improvement of its risk models. This structured testing process ensures that the models remain accurate, reliable, and relevant in assessing credit risks. The second-highest rated statement, "The bank ensures compliance with regulatory requirements when developing credit risk models" (Mean = 3.89, SD = 0.838), suggests that compliance with financial regulations and risk management standards is a key focus in model development. Given the strict regulatory landscape in the banking sector, maintaining adherence to Basel III guidelines and local financial regulations is essential to ensure that risk assessment models meet legal and ethical standards. The statement "The bank continuously develops and refines credit risk models to improve decision-making" (Mean = 3.82, SD = 0.866) ranked third, indicating that the bank actively updates and enhances its credit risk models. However, while this reflects a commitment to innovation, the slightly lower score suggests that there may be opportunities to accelerate or optimize the model refinement process. The statement "Credit risk models are tailored to meet the specific needs of different client segments" (Mean = 3.76, SD = 0.929) ranked fourth, showing that the bank customizes its credit risk

assessment approach based on different customer profiles. However, a relatively lower rating suggests that further personalization or segmentation strategies could be explored to enhance risk prediction for different financial products and customer demographics. The lowest-rated item, "The credit risk model development team collaborates with other departments for data-driven improvements" (Mean = 3.75, SD = 0.931), suggests that while interdepartmental collaboration exists, it could be further strengthened. Effective communication between risk management, finance, IT, and compliance teams is essential to ensure that model development integrates diverse insights and remains aligned with business objectives. The total mean score (19.15) and the high reliability coefficient (0.923) indicate strong internal consistency, confirming that model development is a critical component of the bank's credit risk framework. However, to enhance model effectiveness, the bank should focus on expanding interdepartmental collaboration, refining model customization for different client segments, and ensuring continuous innovation in risk modelling approaches. These efforts will help optimize decision-making accuracy and strengthen the bank's overall risk management strategy.

#### 4.2.2. Decision-Making Processes

Table 8 The results of Decision-Making Processes

| No | Items                                                                                | Mean | SD    | Order | The reliability |
|----|--------------------------------------------------------------------------------------|------|-------|-------|-----------------|
| 1  | Credit risk modelling significantly influences the bank's credit approval decisions. | 3.74 | 0.949 | 1     | -               |
| 2  | The decision-making process has become more data-driven due to credit risk models.   | 3.67 | 0.898 | 4     | -               |

|       |                                                                                                            |       |       |   |       |
|-------|------------------------------------------------------------------------------------------------------------|-------|-------|---|-------|
| 3     | The accuracy of credit risk models enhances the efficiency of financial decision-making.                   | 3.64  | 1.082 | 5 | -     |
| 4     | Credit risk modelling reduces uncertainty and improves confidence in lending decisions.                    | 3.73  | 0.910 | 2 | -     |
| 5     | The use of risk models ensures a balance between profitability and risk mitigation in financial decisions. | 3.71  | 1.011 | 3 | -     |
| Total |                                                                                                            | 18.49 | 4.85  |   | 0.913 |

The findings in Table 9 highlight the role of credit risk modelling in the decision-making processes at SABB (Saudi British Bank). The results indicate that credit risk models play a crucial role in shaping financial decisions, improving accuracy, and enhancing confidence in lending practices. The highest-rated statement, "Credit risk modelling significantly influences the bank's credit approval decisions" (Mean = 3.74, SD = 0.949), confirms that risk assessment models are a key determinant in loan approvals and financial decision-making. This suggests that the bank relies heavily on data-driven risk evaluation before granting credit, ensuring that only financially stable clients receive loans, thereby minimizing defaults and financial losses. The second-highest rated statement, "Credit risk modelling reduces uncertainty and improves confidence in lending decisions" (Mean = 3.73, SD = 0.910), reinforces the idea that data-driven risk assessment provides a structured approach to evaluating creditworthiness. By utilizing risk models, the bank can make more informed and confident lending decisions, reducing the likelihood of financial instability. The statement "The use of risk models ensures a balance between profitability and risk mitigation in financial decisions" (Mean = 3.71, SD = 1.011) ranked third, suggesting that the bank strives to optimize profits while managing credit risks effectively. This balance is critical for maintaining

financial stability and ensuring sustainable lending practices. However, areas for improvement exist. The statement "The decision-making process has become more data-driven due to credit risk models" (Mean = 3.67, SD = 0.898) ranked fourth, indicating that while data-driven decision-making is emphasized, further integration of analytics and AI-driven insights could enhance the process. This suggests a potential opportunity to expand the role of machine learning, predictive analytics, and automated decision-making in risk assessment. The lowest-rated item, "The accuracy of credit risk models enhances the efficiency of financial decision-making" (Mean = 3.64, SD = 1.082), implies that while risk models improve decision-making, there may be occasional inefficiencies or areas where predictive accuracy could be enhanced. This could be attributed to model limitations, evolving financial risks, or gaps in real-time data processing. The total mean score (18.49) and the high reliability coefficient (0.913) indicate that the decision-making processes at the bank are strongly influenced by credit risk models, confirming the critical role of risk assessment in financial decision-making. However, to further enhance efficiency, the bank should consider refining model accuracy, increasing reliance on AI-driven decision-making, and ensuring that risk modelling strategies remain adaptive to market conditions and emerging financial risks.

## **Chapter 5: Discussion and conclusion**

### **5.1. Discussion**

The findings of this study highlight the significant role of credit risk modelling in shaping decision-making processes at SABB (Saudi British Bank). The results indicate that credit risk models improve financial decision-making by reducing uncertainty, enhancing risk assessment accuracy, and ensuring a balance between profitability and risk mitigation. These findings align

with previous research that emphasizes the importance of advanced credit risk assessment frameworks, machine learning models, and real-time data integration in modern banking institutions. The results of this study confirm that credit risk modelling is a critical component of financial decision-making. The highest-rated statement (Mean = 3.74) emphasized that credit risk modelling significantly influences credit approval decisions, reinforcing findings by Celayir & Benli (2023), who noted that global banks heavily rely on structured credit risk models to standardize decision-making and control processes. The ability to quantify and categorize risks effectively allows financial institutions to make more informed and consistent lending decisions, reducing potential financial losses.

Additionally, the study found that credit risk modelling enhances efficiency and data-driven decision-making (Mean = 3.67, SD = 0.898). This is supported by Doko et al. (2021), who highlighted that credit registries and centralized banking data improve the predictive accuracy of risk models, allowing for better segmentation of borrowers and risk assessment of high-risk clients. However, the slightly lower score suggests that banks must continue refining their risk models, integrating external data sources, and utilizing AI-driven analytics to improve credit assessment precision. The results indicate that while credit risk models contribute to improved financial decision-making, challenges remain in optimizing model accuracy and efficiency. This aligns with Montevechi et al. (2024), who reviewed how machine learning (ML) and AI are revolutionizing credit risk modelling by automating assessments and improving predictive performance. AI-powered models can analyze large datasets, detect fraud patterns, and enhance risk classification, making decision-making more precise and adaptable to market fluctuations. Yusof & Roslan (2023) further emphasized that Generative AI and deep learning algorithms have the potential to refine credit risk modelling by predicting borrower behavior more accurately and personalizing

risk profiles. These technological advancements could address some of the challenges in ensuring the accuracy and efficiency of risk models, as highlighted in this study.

Despite the advantages of credit risk modelling, model validation, compliance, and regulatory constraints remain key challenges. The study found that while credit risk models enhance decision-making, they must continuously be refined to keep up with evolving financial risks. Orlova (2019) discussed how banks must establish structured validation processes to test new models, ensuring they remain effective and compliant with financial regulations. This aligns with the findings of this study, where the statement "The accuracy of credit risk models enhances the efficiency of financial decision-making" received a relatively lower rating (Mean = 3.64, SD = 1.082), suggesting that improving model precision remains a priority.

Furthermore, Khalili & Khalilpour (2016) demonstrated that multi-criteria decision-making (MCDM) models can optimize credit risk assessment by classifying customers based on diverse financial and behavioral factors. The study findings suggest that banks must continue to refine their segmentation strategies, ensuring that credit risk models capture a broad spectrum of financial indicators. A crucial aspect of decision-making is ensuring a balance between profitability and risk mitigation. The study found that risk models help banks manage this balance effectively (Mean = 3.71, SD = 1.011). Wu & Hsu (2012) previously explored how hybrid fusion approaches in credit risk modelling improve financial institutions' ability to mitigate risks while maximizing lending opportunities. This supports the notion that financial institutions should integrate risk-based pricing models and dynamic credit scoring approaches to optimize lending decisions. The results of this study, supported by previous research, confirm that credit risk modelling plays a fundamental role in improving decision-making processes at SABB. The findings emphasize that AI-driven analytics, real-time data integration, and structured risk assessment frameworks

significantly enhance financial decision-making. However, challenges remain in ensuring model validation, improving predictive accuracy, and adapting risk assessment strategies to evolving financial conditions. Future research should explore the impact of AI-enhanced risk models, regulatory compliance strategies, and cross-industry comparisons of credit risk assessment methodologies to further refine decision-making processes in banking institutions. By leveraging machine learning, optimizing risk segmentation, and ensuring continuous model validation, banks can enhance decision-making efficiency and maintain financial stability in an increasingly complex financial landscape.

## **5.2. Conclusion**

This study examined the role of credit risk modelling in financial institutions' decision-making processes, with a specific focus on SABB (Saudi British Bank). The findings confirm that credit risk models significantly influence credit approval decisions, improve efficiency, and enhance risk assessment accuracy, ultimately contributing to more data-driven and reliable financial decision-making. The results highlight that technology integration, structured risk assessment, and continuous model development are key components in optimizing credit risk evaluation and minimizing financial losses. However, the study also identified areas for improvement, particularly in enhancing model accuracy, refining customer segmentation, and ensuring continuous model validation to adapt to evolving financial risks. The findings align with previous research, reinforcing that AI-powered analytics, machine learning models, and real-time data integration are transforming credit risk assessment. While the adoption of advanced risk models enhances decision-making efficiency, banks must also focus on regulatory compliance, model transparency, and cross-departmental collaboration to ensure the effectiveness of their credit risk strategies. Overall, this study underscores the importance of credit risk modelling as a critical tool for

financial institutions. By leveraging AI-driven risk assessment, improving predictive accuracy, and refining decision-making frameworks, banks can balance profitability with risk mitigation, ensuring financial stability in an increasingly complex and dynamic banking environment. Future research should explore the integration of AI, regulatory compliance measures, and industry-specific credit risk modelling strategies to further enhance decision-making processes in financial institutions.

### **5.3. Managerial Relevance**

The findings of this study hold significant implications for bank managers, financial decision-makers, and risk management professionals at SABB (Saudi British Bank) and other financial institutions. The study confirms that credit risk modelling plays a vital role in enhancing the accuracy and efficiency of lending decisions, reducing uncertainty, and maintaining a balance between profitability and risk mitigation. Managers should prioritize the continuous development and refinement of credit risk models by integrating AI-driven analytics, real-time data processing, and machine learning techniques. Additionally, investment in employee training and cross-departmental collaboration is essential to ensure that credit risk assessment processes align with regulatory standards and market dynamics. Furthermore, risk management leaders should implement structured model validation frameworks to ensure that credit risk models remain effective and adaptive to evolving financial risks. Strengthening regulatory compliance and transparency in risk assessment methodologies will also enhance trust and reliability in the decision-making process. By adopting a proactive and technology-driven approach to credit risk assessment, financial institutions can improve lending efficiency, minimize default risks, and enhance overall financial stability.

### **5.4. Scientific Implications**

This study contributes to the growing body of research on credit risk modelling, decision-making, and financial risk management. The findings reinforce previous studies on the importance of structured risk assessment frameworks, highlighting how technology, data-driven decision-making, and predictive analytics are transforming the modern banking landscape. From a theoretical perspective, this research supports the integration of AI and machine learning in risk management, aligning with contemporary studies on data-driven financial decision-making. It also validates the significance of model validation, regulatory compliance, and customer segmentation strategies in credit risk assessment. The study further extends knowledge by demonstrating that effective risk assessment models not only reduce financial losses but also optimize decision-making efficiency, bridging the gap between financial risk theory and practical implementation in banking institutions. Future researchers can build upon this work by exploring industry-specific risk modelling strategies, AI-enhanced predictive analytics, and the impact of evolving regulatory frameworks on financial decision-making.

### **5.5. Limitations and Scope for Future Research**

While this study provides valuable insights into the role of credit risk modelling in decision-making at SABB, there are certain limitations that should be acknowledged:

1. **Limited Scope of Industry Analysis** – This study focuses on a single banking institution (SABB), limiting the generalizability of the findings to other banks, financial sectors, and industries. Future research should conduct cross-institutional or cross-sectoral comparisons to identify variations in credit risk modelling strategies.
2. **Cross-Sectional Nature** – The study uses a cross-sectional approach, capturing insights at a single point in time. However, financial risk assessment and decision-making are dynamic processes influenced by economic shifts, regulatory changes, and technological

advancements. Future research should adopt longitudinal studies to analyze long-term trends and the evolving role of AI in risk assessment.

3. Potential Model-Specific Bias – The study assesses credit risk modelling based on SABB's internal framework, which may differ from other banks or financial institutions. Future studies could compare different credit risk models and methodologies to determine their effectiveness across diverse financial institutions and regulatory environments.
4. The Role of AI and Machine Learning – While this study highlights the impact of technology in credit risk modelling, it does not delve deeply into specific AI models and their predictive capabilities. Future research should explore advanced machine learning techniques, deep learning algorithms, and AI-driven risk assessment tools to enhance financial decision-making.

Regulatory and Compliance Considerations – The study does not provide a detailed examination of regulatory frameworks and compliance challenges in credit risk assessment. Given the growing importance of financial regulations (Basel III, IFRS 9, etc.), future research should investigate how regulatory policies impact credit risk modelling and financial decision-making strategies.

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## **Appendix**

# **SURVEY INSTRUMENT**

## **Questionnaire Introduction**

In today's fast-paced and unpredictable world, organizations frequently encounter crises that challenge their stability and continuity. Effective leadership plays a crucial role in navigating these challenges, ensuring that organizations not only survive but also emerge stronger. Leadership during crises involves making decisive actions, maintaining clear communication, and fostering a culture of resilience among employees. Understanding the role of leadership in crisis management is essential for improving organizational preparedness and response strategies. This questionnaire is designed to explore the impact of leadership on crisis management effectiveness and organizational resilience. It seeks to examine how leadership behaviors, decision-making processes, and proactive strategies influence an organization's ability to handle crises and adapt to disruptions. By gathering insights from professionals across different roles and industries, this study aims to provide a deeper understanding of the key leadership attributes that contribute to organizational resilience. The questionnaire is divided into four sections. The first section gathers general demographic and professional background information to understand the diversity of respondents. The second section focuses on leadership, assessing how leaders communicate, motivate, and guide their teams during challenging times. The third section evaluates the effectiveness of crisis management within organizations, including preparedness, training, and response mechanisms. Finally, the fourth section examines organizational resilience, highlighting the ability of organizations to adapt, recover, and implement long-term strategies for sustainability. Your participation in this survey is highly valuable and appreciated. All responses will be kept confidential and used solely for research purposes. By sharing your experiences and perspectives, you will contribute to a better understanding of leadership's role in crisis management and help organizations develop more effective strategies for resilience and recovery. Thank you for your

time and thoughtful responses. Participants will respond to statements. Each section contains a series of statements measured using a **five-point Likert scale**, ranging from **Strongly Disagree (1) to Strongly Agree (5)**, allowing participants to express their level of agreement with each item.

## Section 1: General Information

Please answer the following questions

### Gender:

Male

Female

### Age group:

- ✓ Under 30 years old.
- ✓ 30 –40 years old.
- ✓ 40- 50 years old.
- ✓ 50 or more.

### Educational level:

- ✓ Bachelor's degree
- ✓ Master's degree
- ✓ Doctorate degree

### Years of experience:

- ✓ 1 – 5 years.
- ✓ 6- 10 years.
- ✓ 11- 15 years.
- ✓ 16 or more years.

## 1. Questionnaire terms

Please, mark with (✓) on your selection.

| No                            | Term                                                                                                             | Strongly<br>agree | Agree | Neutral | disagree | Strongly<br>disagree |
|-------------------------------|------------------------------------------------------------------------------------------------------------------|-------------------|-------|---------|----------|----------------------|
| <b>Credit Risk Modelling</b>  |                                                                                                                  |                   |       |         |          |                      |
| <b>Technology Integration</b> |                                                                                                                  |                   |       |         |          |                      |
| 1                             | The bank effectively integrates advanced technologies (AI, big data analytics) to enhance credit risk modelling. |                   |       |         |          |                      |
| 2                             | Automated credit risk models have improved the accuracy of risk predictions.                                     |                   |       |         |          |                      |
| 3                             | The integration of technology in credit risk modelling has reduced manual errors and improved efficiency.        |                   |       |         |          |                      |
| 4                             | The bank continuously updates its credit risk modelling tools to keep up with industry trends.                   |                   |       |         |          |                      |

|                             |                                                                                          |  |  |  |  |  |
|-----------------------------|------------------------------------------------------------------------------------------|--|--|--|--|--|
| 5                           | Employees are well-trained in using technology-driven credit risk assessment tools.      |  |  |  |  |  |
| <b>Risk Assessment</b>      |                                                                                          |  |  |  |  |  |
| 1                           | The bank has a well-structured credit risk assessment framework.                         |  |  |  |  |  |
| 2                           | Risk assessment models accurately identify high-risk clients before approving credit.    |  |  |  |  |  |
| 3                           | The credit risk assessment process is regularly reviewed and improved.                   |  |  |  |  |  |
| 4                           | The bank uses real-time data to assess credit risk effectively.                          |  |  |  |  |  |
| 5                           | Risk assessment results are reliable and contribute to minimizing financial losses.      |  |  |  |  |  |
| <b>C. Model Development</b> |                                                                                          |  |  |  |  |  |
| 1                           | The bank continuously develops and refines credit risk models to improve decision-making |  |  |  |  |  |
| 2                           | Credit risk models are tailored to meet the specific needs of different client segments. |  |  |  |  |  |

|   |                                                                                                          |  |  |  |  |  |
|---|----------------------------------------------------------------------------------------------------------|--|--|--|--|--|
| 3 | There is a structured process for validating and testing new credit risk models.                         |  |  |  |  |  |
| 4 | The credit risk model development team collaborates with other departments for data-driven improvements. |  |  |  |  |  |
| 5 | The bank ensures compliance with regulatory requirements when developing credit risk models.             |  |  |  |  |  |

## Section 2: Decision-Making Processes (Dependent Variable)

|   |                                                                                          |  |  |  |  |  |
|---|------------------------------------------------------------------------------------------|--|--|--|--|--|
| 1 | Credit risk modelling significantly influences the bank's credit approval decisions.     |  |  |  |  |  |
| 2 | The decision-making process has become more data-driven due to credit risk models.       |  |  |  |  |  |
| 3 | The accuracy of credit risk models enhances the efficiency of financial decision-making. |  |  |  |  |  |
| 4 | Credit risk modelling reduces uncertainty and improves confidence in lending decisions.  |  |  |  |  |  |

|   |                                                                                                            |  |  |  |  |  |
|---|------------------------------------------------------------------------------------------------------------|--|--|--|--|--|
| 5 | The use of risk models ensures a balance between profitability and risk mitigation in financial decisions. |  |  |  |  |  |
|---|------------------------------------------------------------------------------------------------------------|--|--|--|--|--|

**Midocean University**

**College of Management**

**Department of Business Administration**

**Proposal Title:**

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Institutions Decision-Making Processes at SABB  
(Saudi British Bank)**

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