Using Expert System in Credit Scoring Analysis

Applied Study on Egyptian Companies Listed in EGX - (Non-Financial Sectors)

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<u>Abstract:</u>

This research aimed to explore the integration of an automated expert systems in credit score analysis in Egyptian companies listed in EGX - (non-financial sectors), focusing on accuracy,

efficiency, and adaptability. To achieve this objective, the researchers applied on 71 from Egyptian listed companies in EGX 100 indicator - Non-Financial Sectors - and the data input was between 2019 to 2022. The study was carried out in two phases, combining theoretical and practical approaches to ensure reliable results. In the first phase, a credit scoring model is developed using insights from previous studies, adapted specifically to the Egyptian financial environment. This model incorporates both qualitative and quantitative methods to capture the complexities of assessing creditworthiness, reflecting real-world credit evaluation scenarios. By addressing financial and non-financial factors, it provides a strong foundation for research. The second phase applies rule-based expert systems to the model. These systems use a set of predefined rules to evaluate creditworthiness, classifying companies into risk categories based on dynamic scoring formulas. The system is tested and refined through simulations and reality trials, ensuring it is adaptable to Egypt's evolving financial landscape. Adjustments are made to optimize its performance, ensuring consistent and accurate results. The study demonstrates significant improvements over traditional methods. The automated expert systems achieve a 99% accuracy rate compared to manual evaluations, reduces data entry errors, and speeds up the evaluation process. It also allows for detailed data classifications, making it easier to compare companies within and across sectors.

By streamlining credit analysis processes, this research highlights the potential for automated expert systems to transform credit risk management. The findings provide valuable insights for financial institutions looking to enhance decision-making and adapt to changing regulatory and market demands.

الملخص :

هدف هذا البحث إلى استكشاف تكامل نظم الخبراء الآلي في تحليل الدرجات الائتمانية في الشركات المصرية المدرجة في البورصة المصرية - (القطاعات غير المالية) ، مع التركيز على الدقة والكفاءة والقدرة على التكيف. ولتحقيق هذا الهدف، قام الباحثون بتطبيق ٧١ شركة من الشركات المصرية المدرجة في مؤشر - EGX100 القطاعات غير المالية - وكانت مدخلات البيانات بين عامي ٢٠١٩ و٢٠٢٢. أجريت الدراسة على مرحلتين ، تجمع بين النهج النظري والعملي لضمان نتائج موثوقة. في المرحلة الأولى، تم تطوير نموذج التصنيف الائتماني باستخدام رؤى من الدراسات السابقة، والتي تم تكييفها خصيصا مع البيئة المالية المصرية. يشتمل هذا النموذج على طرقا نوعية وكمية لالتقاط تعقيدات تقييم الجدارة الائتمانية ، مما يعكس سيناريوهات تقييم الائتمان في العالم الحقيقي. من خلال معالجة العوامل المالية وغير المالية ، فإنه يوفر أساسا قويا للبحث. تطبق المرحلة الثانية أنظمة الخبراء القائمة على القواعد على النموذج. تستخدم هذه الأنظمة مجموعة من القواعد المحددة مسبقا لتقييم الجدارة الائتمانية ، وتصنيف الشركات إلى فئات مخاطر بناء على صيغ تسجيل النقاط الديناميكية. يتم اختبار النظام وتحسينه من خلال عمليات المحاكاة والتجارب الواقعية، مما يضمن قدرته على التكيف مع المشهد المالي المتطور في مصر. يتم إجراء التعديلات لتحسين أدائها ، مما يضمن نتائج متسقة ودقيقة. توضح الدراسة تحسينات كبيرة مقارنة بالطرق التقليدية. يحقق نظام الخبير الآلي معدل دقة ٩٩٪ مقارنة بالتقييمات اليدوية ، ويقلل من أخطاء إدخال البيانات ، ويسرع عملية التقييم. كما يسمح بتصنيفات البيانات التفصيلية ، مما يسهل مقارنة الشركات داخل القطاعات وعبرها.

من خلال تبسيط عمليات تحليل الائتمان ، يسلط هذا البحث الضوء على إمكانات أنظمة الخبراء المؤتمتة لتحويل إدارة مخاطر الائتمان. توفر النتائج رؤى قيمة للمؤسسات المالية التي تتطلع إلى تعزيز عملية صنع القرار والتكيف مع المتطلبات التنظيمية ومتطلبات السوق المتغيرة.

1. Introduction:

The stability of the world’s financial system and the success of a country's monetary policy largely depend on the strength of its financial system, especially banks. Banks, which are key players in risk management, are becoming increasingly crucial due to their connections with global markets and rapid tech advancements. Bank loan approval is a critical and time-consuming process. To manage credit risk effectively, banks must carefully assess customers’ repayment capacity, annual income, and credit score **(Kumar, et al., 2024)**.

The 2007 global financial crisis made it clear that financial institutions and investors need to be more careful with their credit offerings and focus on long-term stability. Being able to foresee credit risks is now crucial for keeping banking systems healthy. This foresight helps protect credit institutions from bad financing decisions and keeps investors from making unwise investments. **(Zavos, et. al., 2023)**

Credit risk significantly impacts banks’ profitability and economic growth, as it involves potential financial losses from borrowers defaulting on loans. Effective credit risk management is crucial to maintaining stability and ensuring sustainable financial performance in the banking sector. **(Kamara, 2024).** It's a major concern because it can lead to non-performing loans, reducing a bank's income and affecting the value of its assets. This risk exists in both the visible and hidden activities of banks. Accurately identifying and measuring credit risk through clear indicators and data is key to managing and minimizing these risks. **(Syadali, et. al., 2023)**

Furthermore, giving loans, the primary income source for banks, is complex and challenging. Banks strive to find customers who can repay their loans. Despite stricter credit policies, some loans still go unpaid. The loan approval process in banks worldwide involves evaluating both financial and non-financial aspects using a credit scoring model. Effective management of credit risk is needed to oversee this process. Later, banks examine non-performing loans to evaluate the effectiveness of their loan granting practices. These procedures help classify customers and decide who gets a loan and how much. **(Abu, 2024)**

On the other side the Artificial intelligence (AI) is transforming various sectors globally, changing the technological scene significantly. Industries like healthcare, retail, and hospitality are increasingly using AI to improve their services. AI helps these industries gather, process, and analyze data to better cater to individual customer needs. Additionally, Customer

Relationship Management (CRM) systems in various sectors are being enhanced with AI to increase customer satisfaction and loyalty, streamline operations, and boost productivity. This shift highlights AI's crucial role in reshaping business strategies and customer interactions. **(Belfguira, 2023)**

So the research focuses on the integration of an automated expert systems, A form of AI Model called in credit score analysis in Egyptian companies listed in EGX - (non-financial sectors), focusing on accuracy, efficiency, and adaptability.

2. Research Problem:

- Timing plays a critical role in ensuring an effective and efficient credit assessment process. In addition to timing, qualitative and quantitative factors must be carefully considered in assessing credit scores. Incorporating these factors enhances the accuracy of credit decision-making, providing a more reliable assessment of creditworthiness.
- The accuracy of using quantitative and qualitative credit risk factors in the assessment process significantly impacts the accuracy and reliability of credit score assessments. Ensuring accuracy in this process can be categorized into three main stages. The first stage is data entry accuracy, which involves reducing the error rate while entering financial and non-financial information. The second stage is data classification accuracy, which ensures that information is correctly classified based on credit-related risk factors. The final stage is data

analysis accuracy, where qualitative and quantitative factors are systematically analyzed to extract meaningful insights that support high-quality credit decisions.

- By focusing on these three stages of accuracy, financial institutions can improve the efficiency, reliability, and effectiveness of their credit risk assessments, ultimately leading to more accurate and informed credit approvals.

3. Research Objectives:

- **Main Goal:** Explore the integration of an automated expert systems in credit score analysis.
- **Sub Goals:**
  - Adapt a credit rating model into automated expert systems.
  - Evaluate the effectiveness and efficiency of the automated expert systems.

4. Research Questions:

- **Main question**: Can the integration of automated expert systems, with credit approval systems effectively solve the main problems of timing and accuracy of credit scoring systems in Egypt?
- **Sub questions:**
  - How can a credit score model be transformed into automated expert systems?
  - How can expert systems enhance the efficiency of credit score systems?

5- Research Importance:

-Academic perspective:

- From an academic perspective, this research topic holds a significant contribution to academic knowledge in credit scoring in the Egyptian banking sector using of expert systems.
- The research will help to understand how expert systems can be utilized in the context of literature application expert systems implementation in credit score.

-Practical / Technical perspective:

- The integration of automated expert systems in credit approval processes can add significant value and benefits to the banking sector in the Egyptian economy.
- More effective and accurate implementation of these systems can help Egyptian banks improve their loan approval processes and enhance overall financial performance, which in turn facilitates access to credit for different types of businesses.
- This improvement can promote economic growth and contribute to the financial stability of the banking sector.

5. Research model data flow used in expert systems:

The expert credit scoring system follows a structured data flow model. The process begins with data entry, where relevant financial and non-financial information is collected. This data is then segmented and classified based on pre-defined criteria to ensure organized processing.

Next, criteria are defined, thresholds and risk indicators are defined that guide the evaluation. These criteria are used to create rules, forming the basis for assessing borrowers' risk levels. The system then applies these rules in the scoring stage, where a credit score is assigned based on logical conditions and structured criteria.

This is followed by score classification, using a grading method to classify borrowers according to risk levels. Finally, the system generates the final score, providing a comprehensive and reliable credit score.

This automated, rule-based approach reduces human bias, reduces processing time, and improves decision-making accuracy. By leveraging structured logic, expert systems provide a scalable and adaptive solution for modern credit risk assessment, ensuring a more robust, data-driven assessment process.

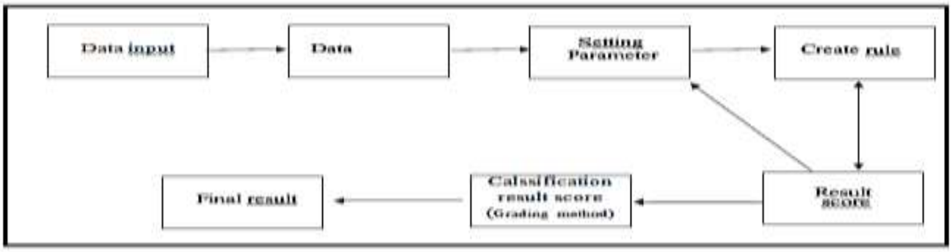


Figure 1

Research model data flow used in expert systems *source by author*

6. Credit risk model:

This credit risk framework provides a comprehensive approach to assessing creditworthiness by integrating financial, commercial, administrative, security, and relationship risks. The structured assessment of these risk categories enables financial institutions to make informed, data-driven credit decisions, minimizing potential losses while ensuring sustainable lending practices.

The researchers added sub-variables to the financial risk influencing factor "activity ratios and market ratios" based on the recommendations of previous studies and the model was

modified to measure the average score for the previous 4 years

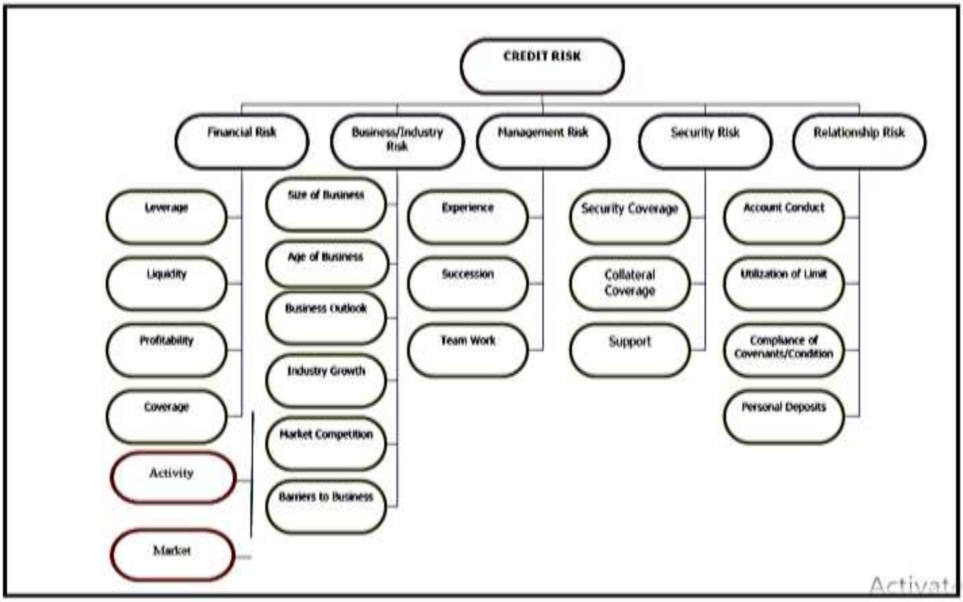


Figure 2 credit risk framework

(source: modified by author based on Bank, B. (2005): Kabir, et. al., (2010)).

7. Theoretical framework of credit scoring

Credit risk refers to the probability that a borrower will fail to meet their financial obligations, leading to losses for the lender. This includes defaults on both principal and interest, disrupting cash flow **(Bussmann, et. al., 2020).** According to (Mohamed, et. al., 2025), credit risk arises when a borrower fails to make payments as promised, which is a significant concern for financial institutions**. (Tsintsadze, et. al., 2019)** define credit risk as the possibility that a borrower may not repay their loan, which affects the lender's cash flow and increases recovery costs. Effective risk management involves evaluating the borrower's financial stability to reduce the likelihood of defaults.

(Jeyaraj, et. al., 2021) highlight that credit risk is evident when borrowers default on obligations such as loans, mortgages, and credit cards. Managing this risk requires choosing reliable borrowers, securing loans with collateral, and using financial models to assess the likelihood of default, based on factors such as portfolio quality and economic conditions.

7.1- Development of the Theory of Credit:

M. Bunge's work Theory of Credit (1852) is one of the earliest comprehensive studies on credit. He defines credit as an exchange where goods or services, to be paid for in the future, serve as the object of exchange. This transaction is based on trust and the expectation of future repayment. Bunge also explores credit from both moral and economic perspectives. In 1868, he established the Kyiv Mutual Credit Association, serving as its chairman until 1871. The Association was a key institution in Kyiv, offering mortgage loans to small businesses and addressing the scarcity of affordable financing. It operated until 1918 and was influential in shaping the credit landscape across the Russian Empire, particularly through its innovative adoption of the Institution of Authorized Representatives **(Lopukh, 2019).**

In modern contexts, credit theories have evolved. In China, the dynamics of urban construction investment bonds are shaped by government policies and fiscal decentralization. Implicit guarantees from local governments, despite lacking formal assurances, influence market perceptions and the creditworthiness of municipal bonds. The 1994 tax-sharing reform and the role of local financing platforms have created a complex relationship between credit risk, policy, and market behavior **(Sichen, 2024).**

Meanwhile, contemporary credit theory, as discussed by (Florian, et. al., 2024), examines how money, laws, and social systems shape credit practices in capitalism. The theory highlights issues such as "monetary sabotage," where financial systems are exploited for private gain, leading to instability and inequality. Credit is increasingly based on intangible assets like patents, reflecting a shift from traditional credit models. Financialization, criticized for prioritizing profits over public good, exacerbates economic inequality, urging a reevaluation of credit's role in modern society.

Finally, **(Li, et. al., 2023)** explore the relationship between commercial credit and risk-taking. Their findings show that when commercial credit is limited, firms avoid risk due to insufficient resources. However, abundant credit empowers firms to take bold investments and pursue growth opportunities, as illustrated by the Substitute Financing Theory.

7.2 Credit risk models:

Credit risk models are essential for banks, helping them measure and manage risks associated with lending. These models assess the likelihood of borrower repayment, thereby reducing potential losses and supporting profitability. The Basel II and III Accords emphasize the importance of strong credit risk models, requiring banks to develop internal systems for estimating regulatory capital. These measures not only help reduce risk but also enhance a bank's reputation and operational efficiency. In recent years, banks have significantly invested in advanced systems to improve how they model credit risk, which aids in evaluating and managing risks across various regions and product lines **(Adamaria, et. al., 2023).**

. Altman's Z-Score:

The Altman Z-score is a vital tool for predicting credit risk, particularly for identifying bankruptcy risk. It provides lenders with insights into a borrower's financial health, with an accuracy rate ranging from 71.21% to 80.30% **(Tatjana, et al., 2024).** The score helps determine if a company is in the "safe," "grey," or "distress" zone:

- A score above 2.60 indicates a 'Safe' zone.
- A score between 1.1 and 2.60 indicates a 'Grey' zone.
- A score below 1.1 indicates a 'Distress' zone.

In 1977, Altman, Haldeman, and Narayanan improved the Z-score model, creating the ZETA score, which combines financial ratios to reflect a company’s financial health. The ZETA score remains widely used, with research showing that it can predict bankruptcy with 90% accuracy, particularly for companies listed on the Kuwait Stock Exchange **(Tatjana, et al., 2024).** The ZETA score uses metrics like return on assets, debt service, liquidity, and capitalization.

In 1995, Altman, Hartzell, and Peck developed the Emerging Market Scoring Model (EMZ-Score), which adapts the original Z-score for emerging markets, incorporating variables like current assets, retained earnings, and book equity to total liabilities. Despite their widespread use, these models face limitations, as they rely heavily on historical financial ratios, making them less effective in rapidly changing economic environments **(Musaed, 2019).**

The Altman model is often criticized for its narrow focus on just five financial ratios, ignoring other factors like stock price movements, market value, and macroeconomic conditions such as inflation and GDP changes. Critics argue that these models do not fully capture the complexities of the economic environments in which firms operate, leading to less reliable predictions, particularly for smaller firms and during periods of economic volatility **(Svatopluk, et al., 2022; Heaton, 2020; Bohdan, et al., 2018).**

. The KMV Credit Monitor Model:

The KMV Credit Monitor Model, derived from options pricing theory by Merton (1974) and Black and Scholes (1973), is another crucial model for assessing credit risk. The model addresses the challenge of evaluating repayment incentives by considering a firm’s asset and equity volatility. The model calculates the Expected Default Frequency (EDF), which indicates the probability of default within a given timeframe, typically one year. The EDF is determined based on the likelihood that the market value of a firm’s assets will fall below the obligations of its debt **(Yang, et al., 2023).**

Originally developed by the KMV Corporation, later acquired by Moody's, the model is now a standard tool for assessing default risks in large corporations. Empirical evidence shows that larger banks have lower levels of asset volatility and are at a reduced risk of default compared to smaller institutions, highlighting the model’s utility in differentiating risk across institutions **(Qingyuan, 2022).**

The KMV model is particularly effective in identifying credit risks and assessing repayment capacity, proving to be a valuable tool for financial institutions in maintaining stability and managing risks effectively **(Jia, et. al., 2024).**

7.3- Credit agencies

Credit Rating Agencies (CRAs) assess the creditworthiness of various entities, including countries, corporations, and financial products such as bonds or money market instruments. The Credit Rating Agency Reform Act of 2006 grants the U.S. Securities and Exchange Commission (SEC) the authority to regulate and oversee Nationally Recognized Statistical Rating Organizations (NRSROs), a designation first applied to CRAs in 1975. Currently, there are 10 CRAs with NRSRO status, which are distinguished by factors such as their coverage, methodology, pricing model, scale, and size **(U.S. Securities and Exchange Commission, 2024).**

In the United States, the dominant CRAs—Moody's, S&P, and Fitch—operate in an oligopolistic market structure. Moody's and S&P collectively rate over 80% of all outstanding issues, with Fitch holding a smaller market share. These CRAs generally operate under the "issuer-pay model," where issuers pay for credit assessments based on a combination of quantitative and qualitative analysis by the CRAs' analysts. Moody's and S&P are key players in empirical analyses, and their rating methodologies and scale types differ slightly. For instance, Moody's includes rating modifiers, whereas S&P assigns a "D" rating to entities in default, while Moody's typically removes ratings for defaulted firms **(CareEdge Ratings, 2024).**

Moody's, founded by John Moody in 1909, is now a subsidiary of Dun & Bradstreet, and it provides credit ratings to evaluate issuers' ability to meet financial obligations. S&P, part of McGraw-Hill, offers credit rating services alongside financial and valuation advisory services and has a long history dating back to the early 20th century.

7.4 - Credit Scoring, Credit Rating, and Sovereign Credit Rating:

In the next section, researchers review the difference between the concepts related to credit, which are credit scoring, credit rating and sovereign credit rating

- Credit Scoring

Credit scoring is a financial evaluation method used to assess an individual’s or organization’s creditworthiness, determining the likelihood of timely repayment of debt obligations. At its core, a credit score is derived from an algorithm that considers various financial factors, such as payment history, outstanding debt, length of credit history, types of credit used, and recent credit inquiries **(Mukhanova, et. al., 2024).** These factors are typically weighted differently depending on the scoring model used, such as FICO or Vantage Score, each providing a numerical representation of credit risk **(Mohammed et al., 2025).**

Credit scores are crucial in financial decision-making as they influence access to credit, interest rates, and loan terms. For individuals, a high credit score reflects a strong financial reputation, granting better borrowing opportunities and lower costs. For businesses, credit scoring helps lenders evaluate repayment risks, often incorporating additional metrics such as revenue stability and market conditions **(Wei, et. al., 2024).**

Modern credit scoring has evolved to include advanced techniques like machine learning, which enhances the accuracy of predicting defaults by analyzing large datasets **(Mukhanova, et. al., 2024).** However, critics argue that traditional credit scoring models may lack adaptability, failing to account for broader macroeconomic factors like inflation or sudden market downturns. Furthermore, reliance on historical data can perpetuate financial inequalities, excluding individuals with limited credit histories from accessing favorable credit terms **(Kuang, et. al., 2024)**.

Ultimately, credit scoring is a dynamic and essential tool for financial risk assessment, offering insights into borrower reliability while continuing to evolve with technological advancements and changing market needs **(Sreekanth, et. al., 2024).**

- Credit Rating

Credit rating is a comprehensive assessment of the creditworthiness of an entity, such as a corporation, government, or financial instrument, reflecting its ability to meet financial obligations. Credit ratings are typically issued by agencies like Standard & Poor's (S&P), Moody's, and Fitch, using a combination of qualitative and quantitative factors. These ratings provide a standardized evaluation of risk, facilitating decision-making for investors, lenders, and policymakers **(S&P, 2024).**

Credit ratings are numerical assessments of a borrower's creditworthiness, evaluating their financial strength concerning a specific debt or financial obligation (Shailesh, 2024). The methodology for determining credit ratings involves analyzing financial stability, debt levels, and market conditions. Ratings are expressed as letter grades, ranging from high-grade (AAA or Aaa) to speculative or junk grades, signifying varying degrees of credit risk (Kuang et al., 2024). These ratings serve as a benchmark for investment quality, influencing interest rates and a borrower's ability to secure financing **(Mukhanova, et. al., 2024).**

Modern advancements in credit rating methodologies incorporate machine learning and big data analytics to improve the accuracy of predictions. These tools enable rating agencies to analyze vast datasets, account for macroeconomic trends, and capture emerging risks in real time **(Mohammed, et. al., 2025)**. However, credit ratings have faced criticism for over-reliance on historical data and static weighting systems, which may not adequately capture dynamic market environments **(Wei. et. al., 2024).**

Moreover, credit ratings play a critical role in global financial markets by signaling economic stability and guiding investment flows. However, concerns about conflicts of interest, particularly in issuer-pays models, have raised questions about the objectivity and reliability of these ratings **(Sreekanth, et. al., 2024).** Despite these challenges, credit ratings remain a fundamental tool in evaluating financial risks and opportunities.

- Sovereign Credit Rating

Sovereign credit ratings assess the financial reliability of a country and its capacity to meet debt obligations. These ratings significantly impact fiscal policy and investment decisions, especially in developing countries. In these regions, the methodologies used by credit rating agencies can sometimes be biased, resulting in negative financial consequences and reinforcing economic subordination (Ramya, 2024). Sovereign credit ratings provide an overview of a nation’s creditworthiness and determine the conditions under which the country can issue new debt. They gauge the likelihood of default, which affects the cost at which governments can borrow and the broader economic conditions **(Michel, 2022).**

A sovereign credit rating also reflects a country's economic performance, political stability, and development level. It serves as a critical indicator of investor confidence, influencing both the decision to invest in the country and the borrowing rates the country faces (Srdan et al., 2022). Essentially, sovereign credit ratings assess the risk of default and shape the yields at which governments can issue debt, playing a vital role in the country's economic stability and international financial relations **(Overes et al., 2021).**

In conclusion, sovereign credit ratings are essential tools for evaluating a country's financial health and risk, influencing everything from debt issuance to foreign investment decisions.

8. Theoretical framework of Expert systems:

In this section, researchers review the theoretical part related to artificial intelligence, machine learning, deep learning, expert systems, types of expert systems, and especially rule-based expert system.

8.1- Artificial Intelligence:

Artificial Intelligence (AI) is a multidisciplinary field aimed at automating tasks that traditionally require human intelligence. By leveraging machine learning algorithms, AI systems analyze data patterns, process language, and create intelligent solutions. These technologies enable machines to autonomously perform complex tasks by learning from new data inputs, leading to intuitive automation **(Pragyna, et. al., 2024).**

AI replicates human cognitive functions like data analysis, decision-making, and language processing. This has driven transformative advancements in industries such as healthcare, finance, and manufacturing, enhancing efficiency, accuracy, and productivity **(Anurag, 2024).**

Emerging in the 1960s, AI has evolved significantly due to global scientific collaboration. Initially focused on numerical data, AI now emphasizes symbolic data processing. A notable application is MYCIN, an expert system designed to identify bacterial infections and recommend treatments based on patient weight, utilizing a backward chaining methodology. This highlights AI's adaptability and its impact across diverse fields **(Bharti, et. al., 2020**

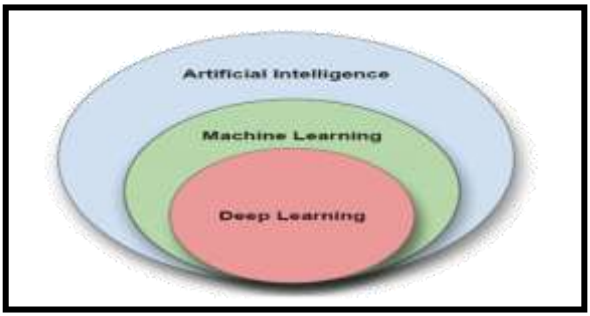


Figure: 3

Relationship between AI, machine learning, deep learning

Source: Artificial Intelligence in Healthcare Industry, P4,2023

8.2 - Machine learning (ML):

Machine Learning (ML), a subset of Artificial Intelligence (AI), focuses on enabling computers to analyze data and learn from it to build predictive models. It uses algorithms to automatically identify patterns, distinguishing between those that learn features from examples and those relying on manually defined features **(Rui, 2024).** ML involves creating statistical models trained on real-world data to predict outcomes or classify observations, improving over time as more data is incorporated **(Luc, et. al., 2022).**

ML allows systems to enhance their performance autonomously, eliminating the need for explicit programming. It has facilitated significant advancements in various fields, such as industrial operations **(Massimo et al., 2021).** It also finds applications in business scenarios like product recommendations, stock market predictions, and language translation **(Carta, et. al., 2021).**

ML employs computational methods inspired by human cognition and decision-making, using statistical and probabilistic techniques. Algorithms in ML are broadly categorized as supervised or unsupervised. Supervised algorithms, in particular, use prior learning to adapt to new data and can identify linear and non-linear relationships within datasets **(Bharti, et. al., 2020).**

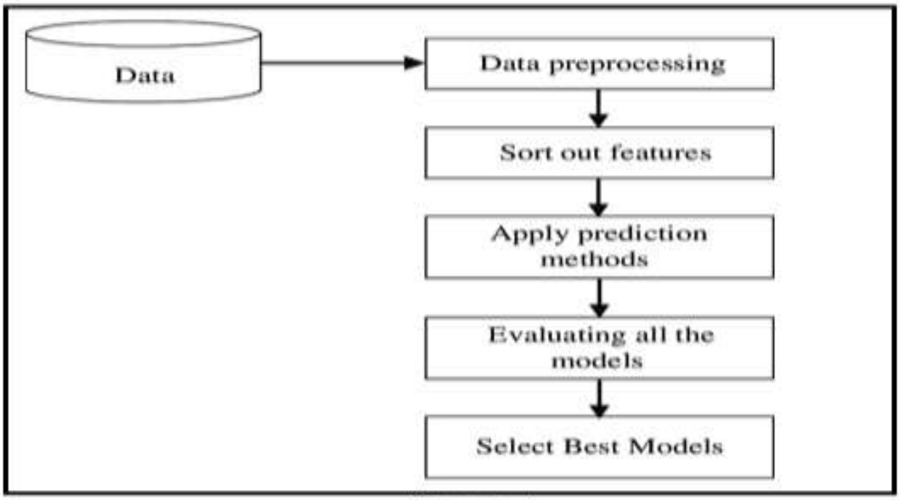


Figure: 4
machine learning structure

Source: Performance Evaluation of Machine Learning Algorithms for Dengue Disease Prediction,2019

8.3- Deep Learning:

Deep learning is a branch of artificial intelligence (AI) and machine learning (ML) that uses neural networks to find patterns in data like text, images, audio, and video **(Alex, 2024).** It's a more advanced type of algorithm that powers applications like language translation and self-driving cars. Deep learning works well with large datasets, though researchers are still trying to understand why it is so effective **(Stephen, 2024).**

It uses multilayered neural networks to achieve high accuracy in tasks like object detection, speech recognition, and language translation. For example, in self-driving cars, deep learning helps analyze huge amounts of data, such as identifying faces in photos and videos **(Bharti, et. al., 2020).**

8.4- Expert Systems:

An expert system is a computer program that copyist the decision-making abilities of a human expert in a specific field. These systems can provide advice, analyze information, make diagnoses, and support professionals by saving time and improving accuracy **(Sevda, 2024).**

- **Where Expert Systems Are Used**

a) Healthcare: Expert systems help doctors by analyzing patient symptoms and medical histories. They use methods like decision trees and rules to suggest possible diagnoses, making medical evaluations faster and more accurate **(Alua, et. al., 2024).**

b) **Other Fields**: Expert systems are used in areas like engineering, business, and gaming, solving problems by using a knowledge base and reasoning like a human specialist **(Waiman, 2024).**

- **How Expert Systems Work (Scikit-learn, 2018):**

a) They follow **if-then rules** to make decisions.
b) They can **infer results** even when data is incomplete.
c) They explain their conclusions and focus on gathering the most relevant information.
d) They have three main parts:

- **Knowledge Base**: Stores important information.

- **Inference Engine**: Makes decisions based on the data.
- **User Interface**: Lets users interact with the system

- **Challenges of Expert Systems (Mahdavifar et. al., 2020).**

a) It's hard to build large, accurate knowledge bases.
b) They don't work well for tasks that need calculations or statistics.
c) They struggle to adapt to new situations.
d) Managing large systems is complex.

- **History and Evolution**

Expert systems were developed in the 1980s to help with medical diagnoses and other tasks. While they were useful, they often made errors and couldn't adapt to new situations. These early systems paved the way for more modern AI methods like deep learning, but their limitations, like replicating human intuition, affected their usefulness in real-world scenarios

(Bharti, et. al., 2020; Mahdavifar, et. al., 2020).

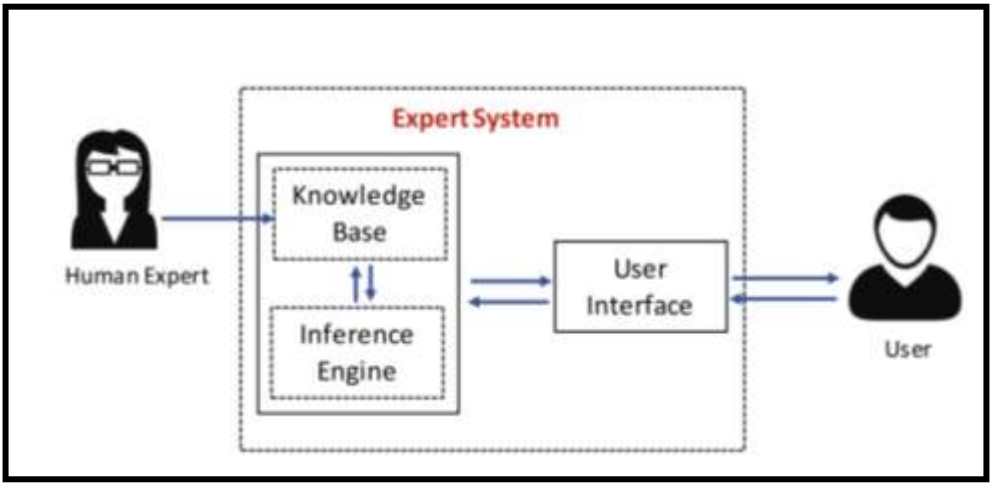


Figure 5
The framework of a rule-based expert system
Source: DeNNeS: Deep Embedded Neural Network Expert System for Detecting Cyber Attacks., 2020

- Characteristics of Expert Systems

Expert systems have several key features that make them effective tools for problem-solving **(Sevda, 2024):**

a) **Knowledge Representation:** Expert systems use structured formats, like rules or facts, to mimic human decision-making and solve problems logically.

b) **Inference Mechanism:** They have an inference engine that reasons through the knowledge base to provide solutions, making them capable of tackling complex problems.

c) **User Interface:** A user-friendly interface ensures that even non-experts can easily interact with the system to get insights.
d) **Domain Specificity:** Expert systems are tailored to specific fields, like medicine or engineering, allowing them to deliver precise, targeted solutions.
e) **Consistency and Reliability:** Unlike human experts, these systems produce consistent results without being affected by emotions, fatigue, or biases.

- Objectives of Expert Systems

The main goal of expert systems is to transfer specialized human knowledge into a computer and make it accessible to users. This involves four main activities **(Bharti, et. al., 2020):**

a) **Knowledge Acquisition:** Gathering and organizing knowledge from experts with the help of a knowledge engineer.
b) **Knowledge Representation:** Structuring knowledge using tools like semantic networks or rule-based systems to make it usable by the system.
c) **Knowledge Inference:** The inference engine applies logic and rules to solve problems using the knowledge base.
d) **Knowledge Verification:** Ensuring the knowledge is accurate and complete through expert validation and iterative refinements.

- Advantages of Expert Systems

Expert systems offer numerous benefits compared to human experts **(Mohammed, et. al., 2019):**

a) Combine expertise from multiple experts for broader insights.
b) Analyze large datasets quickly and comprehensively.
c) Require less training time than human experts.
d) Provide consistent and error-free outputs.

These features make expert systems efficient and reliable tools for solving a wide range of problems.

- Types of Expert Systems

Expert systems come in various types, each suited to different needs **(Mohammed, et. al., 2019):**

a) Knowledge-Based Systems (KBS): Act as on-demand experts, providing consistent advice while saving time and money.
b) Rule-Based Systems: Use "if-then" rules to simulate human reasoning and solve problems systematically.
c) Artificial Neural Networks (ANNs): Mimic the human brain, recognizing patterns and making predictions or classifications from data.
d) Fuzzy Expert Systems: Use fuzzy logic to make decisions with a degree of uncertainty, handling vague and imprecise scenarios effectively.

- History and Structure of Rule-Based Expert Systems

Rule-based expert systems have roots in the production system model developed in the 1970s by Newell and Simon at Carnegie Mellon University. These systems simulate human problem-solving by applying a set of known rules **(Talukdar et al., 2023).**

Core Components of Rule-Based Expert Systems

a) **Knowledge Base:** Contains rules in the form of "if (condition) then (action)" to solve problems or make recommendations.

b) **Database:** Stores facts to be matched against rule conditions.

c) **Inference Engine:** Applies reasoning to connect rules with the database to generate solutions.

d) **Explanation Facilities:** Explains its reasoning and the need for specific information.

e) **User Interface:** Provides users with solutions in an accessible format.

These components work together to create a reliable, human-like decision-making process. Expert systems laid the foundation for modern AI applications, showcasing how knowledge can be structured and applied computationally **(Talukdar et al., 2023).**

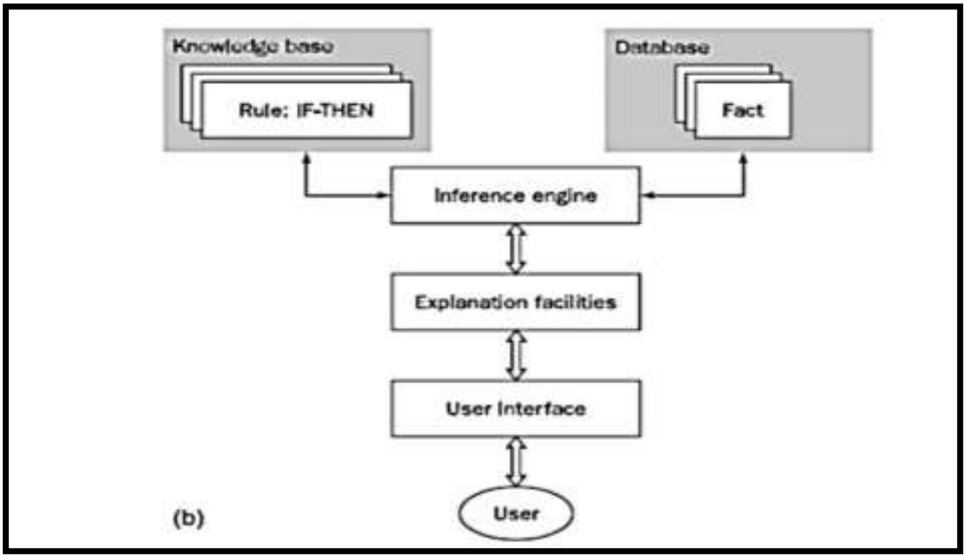


Figure 6
The framework of a rule-based expert systems
Source: Artificial Intelligence in Healthcare Industry Book,2023

9- Empirical studies of credit scoring:

The researchers move on to the next section to review some of the empirical research related to bank risks and credit risks, using artificial intelligence and expert systems in risk management and expert systems in credit score analysis.

9.1 Bank Risks and Credit Risks:

This part reviews key studies on bank risks, credit risks, and the use of artificial intelligence and expert systems in risk management and credit score analysis. The aim is to identify common patterns and insights into risk management in the banking sector.

Banks face many types of risks, such as credit, liquidity, market, operational, legal, compliance, reputation, and strategic risks. Effective risk management strategies are essential.

study by **(Nosheen. et. al., 2024)** examined the critical importance of managing credit risk to ensure the success and stability of banks. A study focusing on banks in Pakistan from 2007 to 2017 how credit risk impacts both conventional and Islamic banks. In Islamic banks, factors like return on equity (ROE), return on assets (ROA), liquidity, the difference between lending and deposit rates (spread), and the size of the bank have a significant relationship with credit risk. Interestingly, the measure of insolvency risk (Z-score) has less impact on Islamic banks compared to conventional ones. For conventional banks, factors such as efficiency, ROA, and bank size are closely linked to credit risk and directly influence overall banking performance. An increase in credit risk is often reflected in a higher ratio of non-performing loans (NPLs), indicating more loans are at risk of not being repaid. The study's findings are valuable for policymakers and banking professionals in Pakistan as they highlight the need for effective credit risk management. By understanding how credit risk affects different types of banks, strategies can be developed to improve the health of the banking sector.

Another study **(Zhao, et. al., 2023)** also confirmed that various risks in bank lending are interconnected, particularly highlighting the impact of leverage risk, Environmental, Social, and Governance (ESG) risks, and liquidity risks. It found that leverage risk led to a significant reduction in loan spreads post-2014, especially affecting nonbank facilities and highly leveraged borrowers. Additionally, it revealed that companies facing higher ESG risks tend to bypass banks for market loans to avoid strict scrutiny, while those with higher ESG ratings often receive better terms from banks with similar high ESG scores. The thesis also linked funding liquidity constraints in banks to reduced stock liquidity, especially during financial crises, providing a deeper understanding of the interplay between leverage, ESG, and liquidity risks in banking.

These studies show the importance of comprehensive risk management strategies and robust internal controls in banks. Effective risk management helps banks adapt to changing conditions and comply with relevant principles and regulations.

9.2 Using Artificial Intelligence and Expert Systems in Risk Management:

Artificial Intelligence (AI) and expert systems have significantly transformed risk management, especially in project management and financial stability assessments.

(Odejide, et. al.,2024) noted that the integration of Artificial Intelligence (AI) significantly transforms project management, particularly in decision-making and risk management. The research explores AI’s capability to analyze vast amounts of project-related data to identify trends and predict outcomes, thus enabling better resource allocation and scheduling. AI's advanced algorithms, such as machine learning and deep learning, are shown to effectively handle both structured and unstructured data, which helps in crafting detailed risk assessments and proactive mitigation strategies. This proactive approach not only enhances decision-making but also fosters a more dynamic response to potential disruptions, thereby increasing overall project success rates.

, The study **(Tangsawasdirat, 2021)** noted that credit scoring models developed for Thai SMEs using financial and non-financial data can effectively predict defaults. Major findings indicate that statistical methods like logit regression, and machine learning methods such as decision trees and random forests, are proficient in assessing credit risk. Particularly, the random forest model was highlighted for its efficacy, while logistic regression models were recognized for their user-friendliness for loan providers. The study emphasizes the need for ongoing development in this area, underscoring the critical role of machine learning and statistical models in the evaluation and management of credit risk.

However, A study (**Teles, 2020)** has suggested that decision support systems significantly enhance credit risk assessment in banking operations involving collateral. By integrating advanced machine learning techniques and statistical models, these systems improve the accuracy of credit scoring. The research underscores the importance of such systems in managing credit risks effectively and suggests that further development could transform credit risk evaluation practices, leveraging the potential of artificial intelligence to refine decision-making processes in financial institutions.

AI and expert systems can improve risk management by enabling more accurate and proactive assessments. Using AI for project data analysis and fuzzy logic for financial stability assessments demonstrates the versatility and effectiveness of these technologies in managing risks.

9.3- Expert Systems in Credit Score Analysis:

Expert systems and advanced algorithms, such as Neuro-Fuzzy models and machine learning techniques, play a crucial role in improving credit score analysis and risk prediction.

(Cavusoglu, et. al., 2023) noted that a novel Neuro-Fuzzy model for credit scoring can effectively classify the creditworthiness of clients by integrating expert opinions and aligning with institutional policies. The research utilized Artificial Neural Networks to generate evaluation metrics for various ANN topologies, assessed through different tuning hyperparameter techniques. Concurrently, a comprehensive evaluation metric hierarchy was constructed using the Fuzzy Analytic Hierarchy Process, combined with a TOPSIS model to determine the optimal neural network topology. This dual-phase methodology leveraged the strengths of both neural networks in credit risk assessment and fuzzy systems to enhance decision-making transparency, highlighting the indispensability of human expertise in validating decisions based on ANN outputs.

The study by **(Tian, et. al., 2022)** revealed significant improvements in predicting delinquencies and defaults among retail consumers and SMEs using a combination of machine-learning techniques and rule-based methods. Analyzing data from 2018 to 2020 within a major business district in China, the research employed nonlinear nonparametric models based on combined datasets of customer transactions and enterprise data. These findings suggest that aggregated credit risk analytics could play a crucial role in forecasting systemic risks. Emphasizing the importance of leveraging historical consumer credit data, especially during pandemic periods, the study indicates that these insights are invaluable for enhancing credit risk assessment models.

In the same context **(Myachin, et. al., 2021)** investigated the development of a fuzzy expert system designed to evaluate the financial security of telecommunications companies. This system uses publicly available data to analyze three key financial indicators: Current Ratio, Equity Ratio, and Return on Assets. By employing fuzzy logic, these indicators are transformed into fuzzy sets to assess the financial stability of the enterprises. The study utilizes the Mamdani fuzzy inference method to compute market concentration and then fuzzifies the output to derive clear, actionable financial security assessments. This approach was tested on three wireline communication companies, effectively demonstrating its capability to provide both numerical and qualitative evaluations of financial health.

Finally study **(Soui, et. al., 2019)** confirmed the effectiveness of a rule-based model utilizing multi-objective evolutionary algorithms (MOEAs) for credit risk evaluation, marking a significant advancement in financial risk assessment. Emphasizing the balance between accuracy and comprehensibility, the research methodologically compared four MOEAs: NSGAII, MOEA/D, SMOPSO, and SPEA2. Notably, the findings highlighted the SMOPSO algorithm as particularly effective in generating classification rules that enhance decision-making transparency in financial contexts, The study also recommended the necessity of using a rules-based system in evaluating credit ratings using more and more complex factors.

The use of expert systems and advanced algorithms greatly enhances credit score analysis and risk prediction. Combining machine learning techniques and rule-based methods provides robust solutions for predicting creditworthiness and managing credit risks, highlighting the need for ongoing development in this area. Despite the progress of research in AI and machine learning-based credit assessment models, the integration of expert systems into credit risk assessment has a gap. Therefore, our research will focus on developing a modified credit risk model and integrating it with expert systems, which will enable more accurate, transparent and adaptive risk assessments in financial institutions. In this context, we review some selected studies that integrated credit models and that relied on important determinants with different used AI tools in addition to the samples used in each study to highlight the importance of choosing a credit model as well as relying on expert systems. The following tables show these studies:

Table 1: Selective literature of credit risk factors

Authors	Method	Sample	Significant determinants
shbaugh-Skaife, Collins, and LaFond (2006)	Ordinary regression and speculative grade analysis	2000 firms with varying corporate governance quality rated by S&P; profiles on 22,000 individual directors	Number of Outside Blockholders, Accrual Quality, Earnings Timeliness, Board Independence, CEO Power, Insider Ownership, Board Expertise, Leverage, Return on Assets, Net Income Before Extraordinary Items, Size, Subordinated Debt, Interest Coverage
Sih (2006)	Generalized Estimating Equations model, considering panel data	U.S.-operating firms	Industry Type, Cash, Market Value
Gray, Mirkovic, and Ragunathan (2006)	Ordered probit models	Australian companies rated by S&P between 1995-2002	Interest Coverage, Leverage, Profitability, Industry Concentration
Sales (2006)	Ordered probit models	44 Brazilian banks	Total Assets, Equity, Deposits, Gross Profit, Net Profit, Operating Profit
Bone (2007)	Ordered logit model for rating forecast	Petrobras oil and gas companies (2007)	Interest Coverage, Short-term Debt/Total Debt
Shiu and Chiang (2008)	Ordered probit regression, ordered logit model for robustness check	Companies in the Lloyd's Market	Leverage, Reinsurance, Concentration Index, Profitability, Liquidity, Growth, Size
Matousek and Stewart (2009)	Ordered probit model with dynamic factors	681 international banks	Equity/Total Assets, Liquidity, Size, Net Interest Margin, Operating Expense/Operating Profit, Return on Assets
Bone (2010)	Ordered logit models, ordered probit models	Repsol-YPF (2010)	Interest Coverage, Short-term Debt/Total Debt
ouzada et al. (2012)	Logistic Regression Models	4,504 Brazilian consumer loans in a commercial bank	Client type, gender, age, marital status, length of residence
Bekhet and Eletter (2014)	Logistic Regression Model, Radial Basis Function Scoring Model	492 accepted and rejected applications in different Jordanian Commercial Banks	12 financial and non-financial variables related with consumer loans
Darwish & Abdelghany (2016)	Fuzzy Logic Model	real data from Egyptian CIB bank.	Profitability, Debt-paying ability, Operation ability , Liquidity
Authors	Method	Sample	Significant determinants
Yusof, Alias, Kassim and Zaidi (2021)	KMV-Merton model	Four Malaysian firms (2014 – 2019)	liquidity, solvency, indebtedness, return on asset (ROA), and interest coverage.

Myachin, Yudina and Myroshnychenko 2021	**fuzzy expert system**	**3Ukrainian firms of telecommunications enterprises**	**Current Ratio, Equity Ratio, Return on Assets (ROA)**
Modisane et al. (2024)	**data collection, statistical analysis, case studies, comparative analysis**	**Comprehensive banking sector data**	**Debt-to-asset ratios, income changes, general economic indicators, regulatory changes, and technological innovation.**

Source (Le, 2019) and completed through by author

This table presents a review of key studies on credit risk factors, highlighting the methodologies, sample data, and significant determinants identified by various researchers. And based on the previous table we find that

- Leverage, interest coverage, profitability, and liquidity are commonly identified as significant determinants of credit risk.
- Different studies apply regression models, probit models, and logit models to analyze corporate and banking credit risks.

Table 2: Literature review on the use of financial ratios

Author	Main idea of research
Frederiksust (2001)	Predicted corporate failure based on liquidity, profitability, solvability, industry, and economic variables using data from failed Dutch firms.
Trenvino (2002)	Suggested that the price-earnings ratio is highly correlated with future stock return, though it is subjective and depends on investor expectations.
Arnott (2003)	Found a high correlation between increasing earnings per share and increasing payout ratios from 1946 to 2001.
Lewellan (2004)	Demonstrated that financial ratios are still a valid tool for stock price prediction in modern economic environments.
Alfaro et. al. (2008)	Used an alternative method (AdaBoost and neural networks) for corporate failure prediction, comparing empirical models.

Uyar and Okumus (2010)	Investigated the impact of the 2008 financial crisis on Turkish industrial enterprises using financial ratios.
Yu and Wenjuan (2010)	Used decision trees to examine financial ratios influencing profit growth in logistics companies.
Siekelová (2017)	Confirmed the effectiveness of credit ratings in measuring credit risk by integrating both quantitative and qualitative factors. Developed a methodology for calculating credit risk based on financial indicators.
Saygili et. al. (2019)	Highlighted the role of credit scoring for SMEs in accessing financing, emphasizing financial and non-financial factors like liquidity ratios and the age of major shareholders.
Angeline et. al. (2021)	Examined firm-specific factors affecting credit rating changes. Used the Ordered Probit model to analyze factors like the interest coverage ratio.
Modisane et. al. (2024)	Emphasized the importance of various factors influencing credit risk management and financial performance. Found that incorporating weights of evidence improves credit risk prediction models.

Source (Le, 2019) and completed through by author

This table presents a review of key research studies focusing on corporate failure prediction, financial ratios, credit risk assessment, and credit scoring methodologies.

Important points:

- Corporate failure prediction relies on financial indicators like liquidity, profitability, and solvability.
- Financial ratios remain critical tools for predicting stock prices, credit ratings, and corporate stability.
- Machine learning and alternative models (AdaBoost, Neural Networks, Decision Trees) enhance credit risk prediction.

- Credit scoring for SMEs is vital for access to financing, with a growing focus on qualitative factors.
- Modern AI-driven methodologies (weights of evidence, ordered probit models) improve risk assessment accuracy.

10. Methodology

This research introduces an updated to the best of researcher knowledge it divided this approach divided into three main phases. Each phase is different but connected, helping to validate our ideas through real data.

Phase 1: Model Methodology Based on Credit Score Framework

This phase focuses on developing a model inspired by previous studies, tailored specifically to companies listed in Egypt.

- **Data Collection and Analysis:** Both qualitative and quantitative methods are used to gather and validate data.
- **Objective:** To mimic real credit evaluation scenarios and address the complexities of assessing creditworthiness in the Egyptian financial sector.
- **Outcome:** A foundational model capturing key features of credit scoring to serve as a basis for further application.

Phase 2: Application to Rule-Based Expert Systems

The second phase applies rule-based expert systems to enhance the credit analysis process.

- **How It Works:** The developed model is translated into rules that define what makes a company creditworthy.
- **Testing:** The systems are tested through simulations and real-world trials to assess and fine-tune their performance.
- **Goal:** To ensure these systems adapt effectively to Egypt's dynamic financial landscape, improving accuracy and decision-making in credit analysis.

Number	Risk components	Components weights	Parameters		P. Weights
1	Financial Risk	50%	Liquidity = 10	Current Ratio	5
				Quick Ratio	5
			Activity = 10	Cash conversion cycle	10
			Profitability = 10	Operating profit margin	2.5
				Net profit margin	2.5
				Return on investment	2.5
				Return on equity	2.5
			Leverage = 15	Debt to equity	4
				Debt to asset	3
				Long term debt to assets	3
				Coverage	5
			Market = 5	Price / Earnings	2.5
				Market / Book	2.5

This dual-phase methodology ensures the research findings are both reliable and practically applicable for improving credit evaluation practices in Egypt.

10.1 - Model Methodology

The *"Credit Risk Grading Manual"* by **(Bank. B. 2005: Kabir, et. al., 2010)** provides the foundation for this phase. It introduces a structured framework for assessing and grading credit risk in banking, emphasizing a systematic approach for effective risk management.

The methodology evaluates creditworthiness by analyzing five key risk areas, each weighted and assessed to derive an overall risk grade:

- Financial Risk Evaluation

This assesses risks arising from financial instability, focusing on:

a) Leverage, liquidity, profitability, interest coverage ratios, and the cash conversion cycle.

b) Identifying risks associated with high debt, poor cash flow, low profitability, or weak liquidity.

c) The **cash conversion cycle** is particularly important, as it reflects financial deficits and is widely used in literature.

- Business/Industry Risk Evaluation

This evaluates risks tied to industry conditions or business challenges, such as:

a) Industry growth, market competition, business size, and market entry/exit barriers.
b) Identifying risks from low market share or stagnant industry growth.

- Management Risk Evaluation

This focuses on risks linked to managerial deficiencies, assessing:

Management experience, succession planning, and teamwork effectiveness.

- Security Risk Evaluation

This evaluates the quality and adequacy of collateral in case of default, considering:

Collateral valuation, location, and overall security strength.

Table 3: Components and Weights of Credit Risk Factors

2	Business/Industry	18%	Size of Business	5
			Age of Business	3
			Business Outlook	3
			Industry growth	3
			Market competition	2
			Entry/Exit Barriers	2
3	Management Risk	12%	Experience	5
			Succession	4
			Team Work	3
4	Security Risk	10%	Security coverage	4
			Collateral coverage	4
			Support	2
5	Relationship Risk	10%	Account conduct	5
			Utilization of limit	2
			Compliance of covenants	2
			Personal deposit	1
	Total score			100

- Relationship Risk Evaluation

This assesses the borrower’s history and interactions with the bank, focusing on:

Credit limit utilization, account performance, and compliance with terms.

The previous table shows the credit model, the main factors” risk component “for evaluation, and the sub-factors” parameters“for each main factor, with a weight for each of the main and sub-factors. We then move on to review a table showing the grade of assessment based on actual assessment which is equal between 0:100.

Table 4: Credit Score Grade

Number	Risk Grading	Short Name	Score
1	Superior	SUP	100
2	Good	GD	85+
3	Acceptable	ACCEPT	75-84
4	Marginal/Watchlist	MG/WL	65-74
5	Special Mention	SM	55-64
6	Sub-standard	SS	45-54
7	Doubtful	DF	35-44
8	Bad & Loss	BL	<35

(Source: Kabir, et. al.,2010)

Source: (Kabir, et. al.,2010)

(source: modified by author based on Bank, B. (2005): Kabir, et. al., (2010))

A. Superior (SUP) - Grade 1

- **Description:** Credits are exceptionally secure, backed by full cash coverage, government guarantees, or top-tier international banks.

B. Good (GD) - Grade 2

- **Description:** Credits backed by borrowers with excellent repayment capacity, strong liquidity, low debt, consistent earnings, and a solid market position.
- **Guarantee:** Often guaranteed by top-tier local banks.

- **Score:** 85 or higher.

C. Acceptable (ACCPT) - Grade 3

- **Description:** Credits from borrowers with stable but not exceptional performance.
- **Features:** Adequate liquidity and secured with acceptable collateral.
- **Score:** 75 to 84.

D. Marginal/Watchlist (MG/WL) - Grade 4

- **Description:** Credits requiring closer monitoring due to increased risk factors.
- **Score:** 65 to 74.

E. Special Mention (SM) - Grade 5

- **Description:** Credits showing potential weaknesses that need management attention.
- **Score:** 55 to 64.

F. Substandard (SS) - Grade 6

- **Description:** Credits with doubtful repayment capacity, indicating financial vulnerability.
- **Risk Level:** High risk of loan settlement issues.
- **Score:** 45 to 54.

G. Doubtful (DF) - Grade 7

- **Description:** Indicates a high probability of non-repayment of principal and interest, with losses likely.
- **Features:** Not classified as irrecoverable but significant risk due to factors like litigation.
- **Score:** 35 to 44.

H. Bad & Loss (BL) - Grade 8

- **Description:** Represents severe financial issues or near liquidation, with minimal recovery chances.
- **Action:** May require write-off pending security liquidation.
- **Score:** Below 35.

10.2- Research model data flow used in expert system

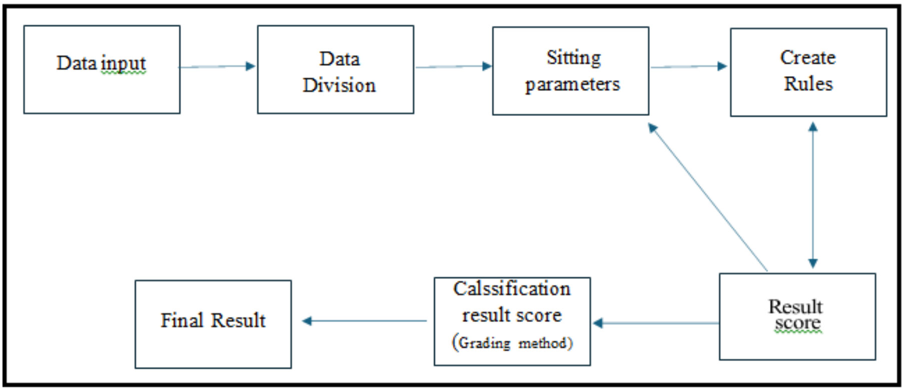


Figure 1
Research model data flow used in expert system source by author

The credit scoring process in a rule-based expert systems follows a structured workflow designed to automate and enhance the accuracy of credit assessments. It begins with a data entry phase, where credit-related information is collected. This data is then divided into data categories to ensure a strong analytical basis for accurate predictions. Once the data is prepared, the system moves to the parameterization phase, where key criteria and conditions for credit scoring are configured. Based on these parameters, specific rules are created to guide the assessment process. These rules are then applied to calculate an initial credit score, known as a score. To ensure meaningful interpretation, the system categorizes this score into a rating system, assigning a category that reflects the borrower's creditworthiness. Finally, the process culminates in the assignment of a final credit score, which provides a comprehensive and automated assessment of credit risk. By structuring the process in this way, the expert systems enhances the decision-making process by ensuring consistency, accuracy, and efficiency in the assessment of credit applications.

10.3 - Population and Sample:

At this stage, researchers move on to reviewing the study population and the sample subject to testing and measurement

10.3.1 - Population: Egyptian Listed Companies

The study focuses on all companies listed on the **Egyptian Listed Companies,** representing various industries and sectors. These companies reflect the dynamics of the Egyptian economy and market regulations, making them an ideal population for research on corporate performance, governance, and economic impact

10.3.2 - Sample: EGX100 (Non-Financial Sectors)

The sample consists of companies from the EGX100, excluding those in the financial sector. The EGX100 comprises the top 100 companies by market capitalization and liquidity, providing a strong representation of Egypt's corporate activity. Focus on Non-Financial Sectors: By excluding financial companies, the study concentrates on manufacturing, technology, services, and healthcare industries. This ensures a broader creditworthiness analysis while avoiding the financial sector's unique complexities, which require specialized methodologies. This targeted approach allows for a comprehensive assessment of credit scoring across diverse industries in Egypt.

Table 5 : Companies sample: EGX 100

number	Company Name	Sector
1.	Tenth Of Ramadan Pharmaceutical Industries&Diagnostic-Rameda	Pharmaceutical
2.	Cleopatra Hospital Company	
3.	Ibnsina Pharma	
4.	Egyptian International Pharmaceuticals (EIPICO)	
5.	Al Tawfeek Leasing Company-A.T.LEASE	Real Estate
6.	Development & Engineering Consultants	
7.	El Shams Housing & Urbanization	

8.	Emaar Misr for Development	
9.	Heliopolis Housing	
10.	Ismailia Development and Real Estate Co	
11.	Mena Touristic & Real Estate Investment	
12.	Palm Hills Development Company	
13.	Pioneers Properties For Urban Development(PREDCO)	
number	Company Name	
14.	Orascom Development Egypt	
15.	United Housing & Development	
16.	Zahraa Maadi Investment & Development	
number	**Company Name**	**Sector**
17.	Medinet Nasr Housing	Real Estate
18.	El Kahera Housing	
19.	Egyptians Housing Development & Reconstruction	
20.	Sharm Dreams Co. for Tourism Investment	Travel & leisure
21.	Misr Hotels	
22.	Egyptian for Tourism Resorts	
23.	Ezz Steel	Basic resources
24.	Abou Kir Fertilizers	
25.	Kafr El Zayat Pesticides	
26.	Egyptian Chemical Industries (Kima)	
27.	Misr National Steel - Ataqa	
28.	Paint & Chemicals Industries (Pachin)	
29.	Sidi Kerir Petrochemicals - SIDPEC	
30.	Egypt Aluminum	
31.	Asek Company for Mining - Ascom	
32.	Misr Fretilizers Production Company - Mopco	
33.	Elswedy Electric	Industrial goods & service automobile
34.	Gadwa For Industrial Development	
35.	GB Corp	
36.	Natural Gas & Mining Project (Egypt Gas)	utilities

37.	E-finance For Digital and Financial Investments	It , media & communication
38.	Egyptian Media Production City	
39.	Fawry For Banking Technology And Electronic Payment	
40.	Orascom Investment Holding	
41.	Telecom Egypt	
42.	Alexandria Mineral Oils Company	Energy & Support
43.	Egyptian Transport (EGYTRANS)	services
44.	MM Group For Industry And International Trade	Trade & distribution
45.	United Arab Shipping	Shipping & Transportation services
46.	Canal Shipping Agencies	
47.	Alexandria Containers and goods	
48.	Al Khair River For Development Agricultural Investment&Envir	Food , Beverages and Tobacco
49.	Obour Land For Food Industries	
50.	AJWA for Food Industries company Egypt	
51.	Raya Contact Center	
52.	Edita Food Industries S.A.E	
53.	Delta Sugar	
number	Company Name	
54.	Eastern Company	
55.	The Arab Dairy Products Co. Arab Dairy - Panda	
56.	Ismailia Misr Poultry	Food , Beverages and Tobacco
57.	Juhayna Food Industries	
58.	Cairo Poultry	
59.	Maridive & oil services	
60.	Taaleem Management Services	Education services
61.	Nasr Company for Civil Works	Contracting &

62.	**Giza General Contracting**	**construction engineering**
63.	**The Egyptian Company for Construction Development-Lift Slab**	
64.	**Orascom Construction PLC**	
65.	**El Nasr Clothes & Textiles (Kabo)**	**Textile & Durables**
66.	**Alexandria Spinning & Weaving (SPINALEX)**	
67.	**Dice Sport & Casual Wear**	
68.	**Arab Cotton Ginning**	
69.	**Oriental Weavers**	
70.	**Misr Cement (Qena)**	**Building Material**
71.	**El Ezz Porcelain (Gemma)**	

source by author

10.4- Testing and validation

After preparing modifications to the model, the author tested the model on some companies to look at the possibility of application, conformity, and the extent of the availability of information as a verification stage. Before the second step, figures (6&7) and table (3)show the extent of the possibility of application and use.

Figure 6
testing on sample
(source: by author)

Figure 7
testing on sample
(source: by author

10.5 - System Application:

The proposed credit scoring system leverages **Microsoft Dynamics**, chosen for its versatile tools like Excel, Power PE, and Microsoft Forms, offering an easy-to-use interface that doesn't require coding. The application process is broken down into key components:

- 10.5.1 - Database

The database is the foundation for evaluation and must be clearly structured for data entry and processing. The process includes:

1. **Data Division:**

- Data is categorized according to credit risk components (referenced in Figures 8, as outlined in the methodology model.

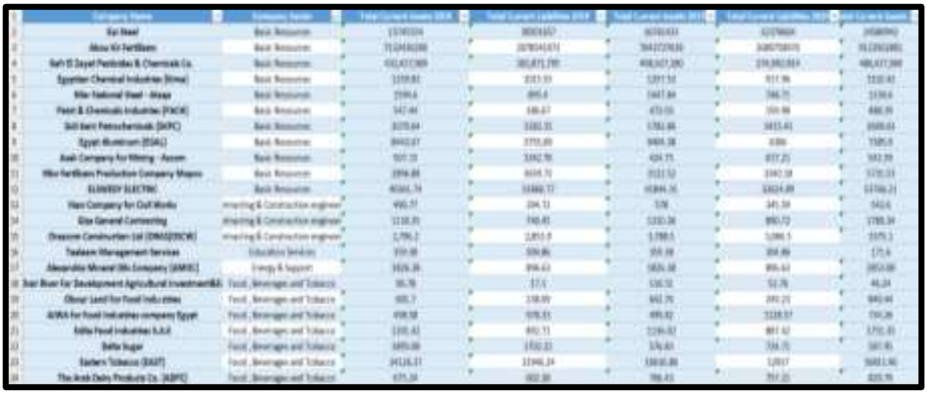


Figure 8
data division
source by author

2- Data Entry:

- Microsoft Forms was used to create a structured form for collecting credit analysis data.
- Data is exported into Excel format, with closed and open-ended questions designed based on credit risk components (as shown in Table 3 and Figures 9&10).
- The form supports initial analysis, allowing for efficient data entry and transfer.

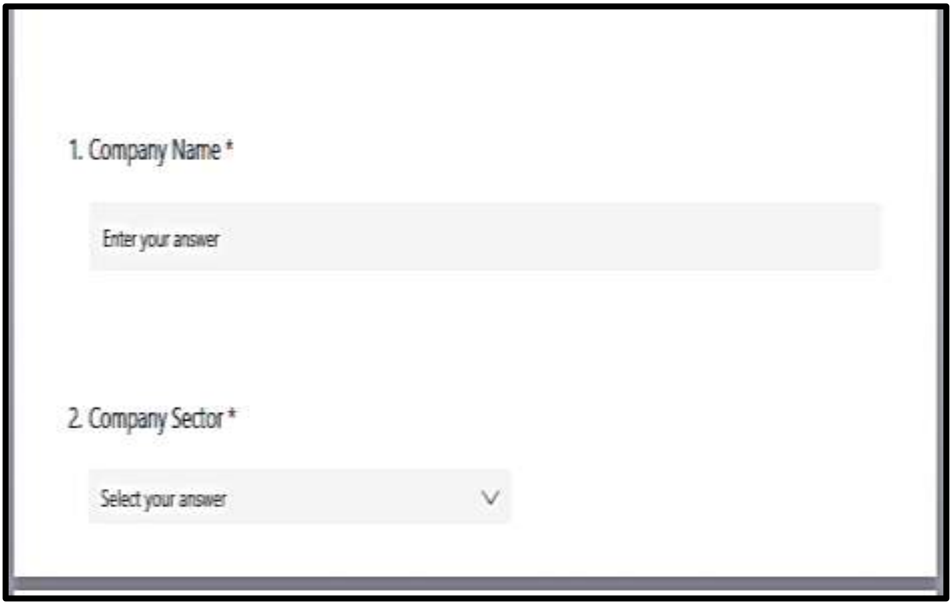


Figure 9

data division

source by author

2 Data Preparation:

- The entered data is organized according to the initial model Compatibility and arrangement are demonstrated in Figure 10&11

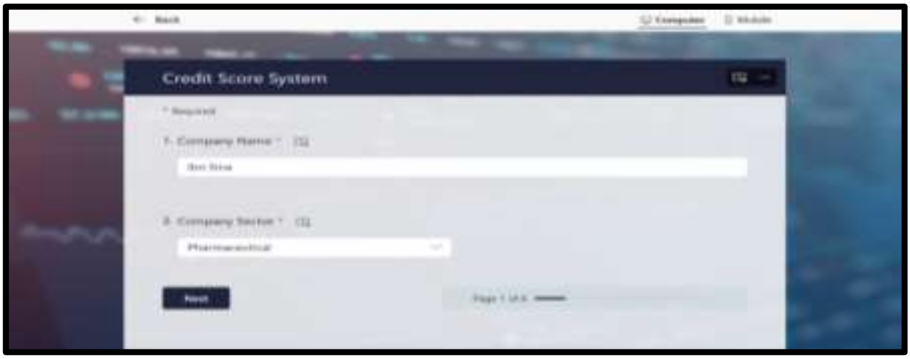


Figure 10

data input interface

source by author

Figure 11

ability to transfer into excel

source by author

10.5.2 - Rule Base

The rule base uses Excel to manage data rows and columns with mathematical operations and functions. The process includes:

Data Classification: Organizing data types (Table 3):

- **Equations for Financial Parameters (Table 3)**

Data Type	Qualitative or Quantitative
Financial data	Quantitative
Business & industry data	Qualitative & Quantitative
Management data	Qualitative
Security data	Qualitative
Relationship data	Qualitative

Table 6 : Data type

source by author

parameter	detail	equations
Liquidity	Current Ratio	Current assets / Current liabilities
	Quick ratio	(Current assets – inventory) / Current liabilities
Cash conversion cycle	CCC	(DIO + DSO) – DPO
Profitability	Operating Profit Margin	Operating profit / Net Sales %
	Net Profit Margin	Net profit / Net sales %
	ROE	Net profit / Total Equity %
	ROI	Net profit / Total Assets %
Leverage	Debt to Equity	Total liabilities / Total Equity
	Debt to Assets	Total liabilities / Total Assets
	Long Term Debt to Assets	Long Term liabilities / Total Assets
	Interest Coverage Ratio	operating profit / Finance expenses
Market	P/E	Market price per share of common stock / Earnings per share
	M/B	Market price per share of common stock / Book value per share of common stock
Size of business	Sales growth	(Ending sales – beginning sales) / beginning sales*100

Table 7 – Financial Parameters equations

10.5.3 - Inference Engine

At this stage, data is matched against rules to generate results. The process involves:

1. **Data Integration:**

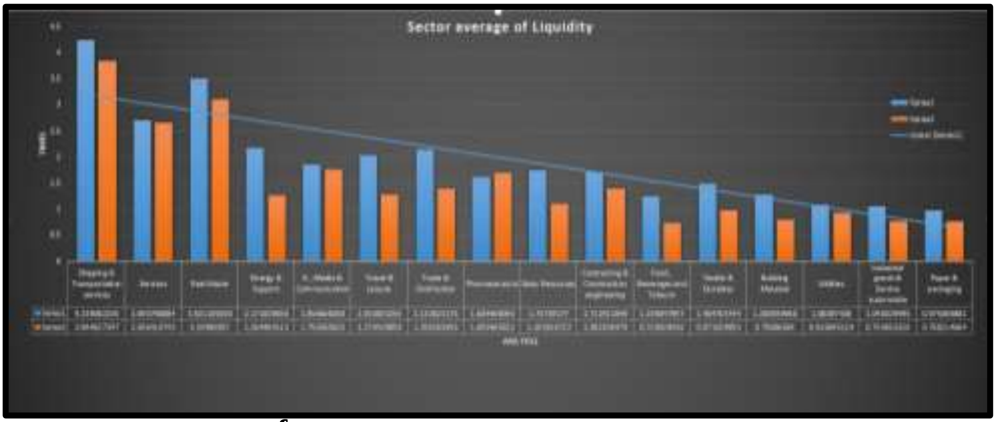
- Each credit risk component (e.g., Financial, Industry, Management) is evaluated separately on a spreadsheet.

2. **Risk Assessment:**

- Components are aggregated into a total score, which is then classified into categories like 'Good' (GD), 'Acceptable' (ACCP), or 'Marginal/Watchlist' (MG/WL) based on predefined formulas.

3. **Output:**

- A comprehensive risk assessment is compiled for companies across sectors like Basic Resources, Food & Beverages, and Construction & Materials.
- The spreadsheet functions as an analytical and decision-making tool, categorizing companies based on total risk scores to guide credit analysts and risk managers.



sector average transfer

source by author

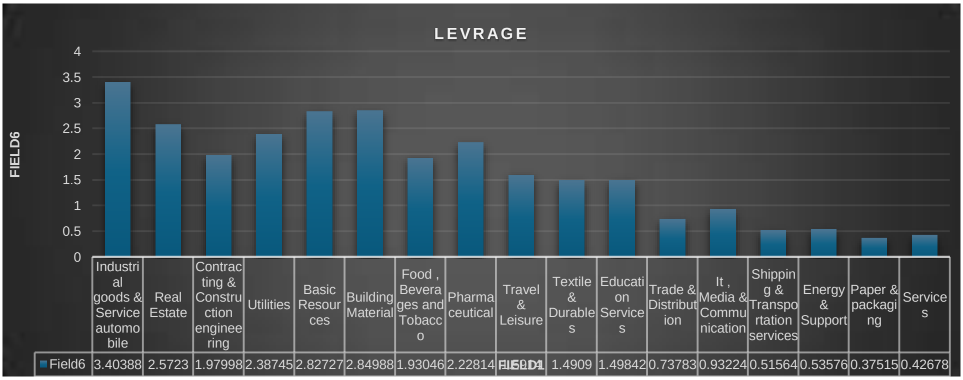


Figure 13

sector average transfer

source by author

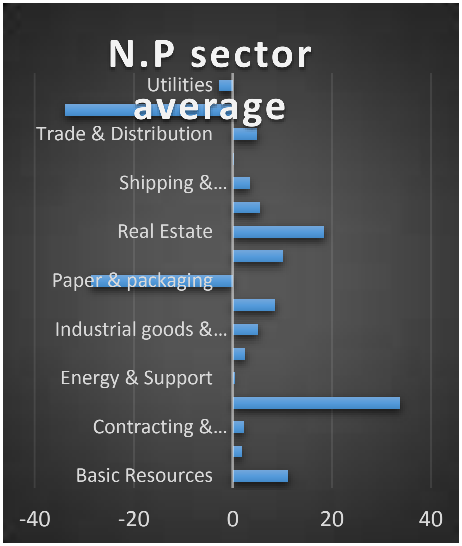


Figure 14
N.P sector average
source by author

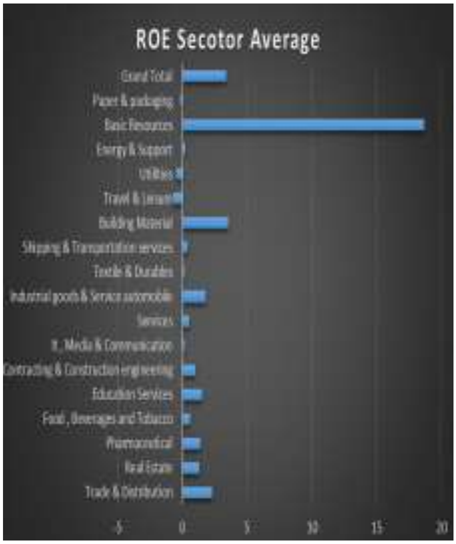


Figure 15
ROE sector average
source by author

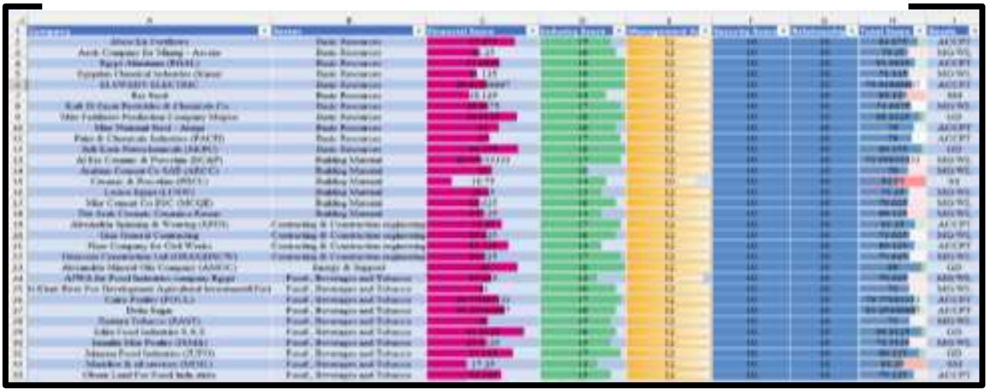


Figure 16
total score sheet
source by author

10.6- System design:

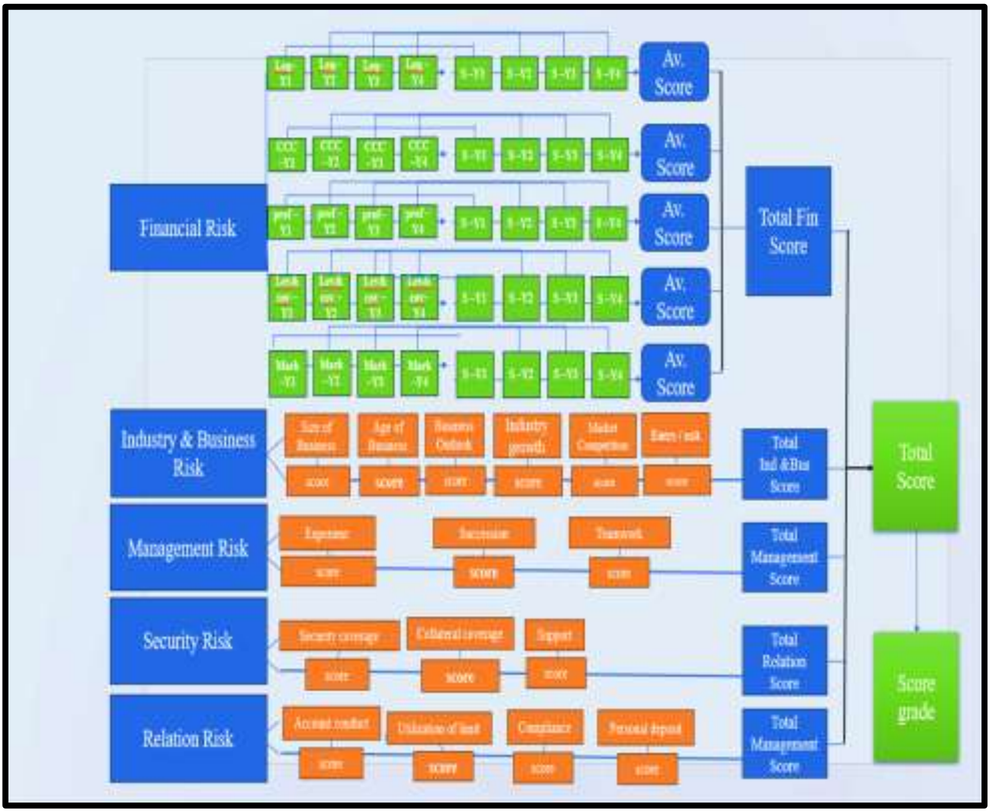


Figure 17
System design
source by author

10.6 - System Design

The system design organizes credit evaluation into a detailed framework, breaking down risk into key categories, scored annually and averaged for financial metrics.

Risk Categories:

1. **Financial Risk:**
- Evaluated using metrics like debt levels, profitability, liquidity, and cash conversion cycles.
- Yearly data is averaged to provide a clear financial risk score, enhancing Saha's annual-only model.

2. **Business/Industry Risk:**
- Consider factors like company size, industry growth, competition, and market entry barriers.

3. **Management Risk:**
- Focuses on leadership experience, succession planning, and teamwork effectiveness.

4. **Security Risk:**
- Assesses the adequacy and quality of collateral.

5. **Relationship Risk:**
- Examines the company's interactions with the lender, including account performance and rule compliance.

Total Score and Grade Conversion:

- All risk scores are combined into a **Total Score**, which is converted into a **Score Grade** (e.g., GD, ACCPT).

- This streamlined approach supports informed lending decisions by offering a clear classification of a company's risk profile.

11- Finding

11.1- Transformation of a Credit Score Model into Automated Expert Systems

Based on the details provided in the third chapter, "Methodology," it's clear that the credit scoring model has been updated to an automated expert systems. This updated system uses a complex spreadsheet to carry out a thorough risk assessment across various industries such as Basic Resources, Food & Beverages, and Construction & Materials. Each company is carefully evaluated on a scale in five main risk categories: Financial, Industry, Management, Security, and Relationship.

The system uses dynamic formulas set up in the top row of the spreadsheet to automatically determine each company's risk category based on its total risk score. These categories include 'MG/WL' for marginally acceptable, 'GD' for good, and 'ACCP' for acceptable. This automated system provides a consistent and unbiased way to assess and categorize company risks, helping to make more informed decisions in credit scoring.

1	Company	Sector	Financial Score	Industry Score	Management Sc	Security Score	Relationship	Total Score	Grade
2	Abou Kir Fertilizers	Basic Resources	[illegible]	15	12	10	10	84.875	ACCPT
3	Asek Company for Mining - Ascom	Basic Resources	[illegible]	16	12	10	10	70.25	MGWL
4	Egypt Aluminum (EGAL)	Basic Resources	[illegible]	18	12	10	10	81.0625	ACCPT
5	Egyptian Chemical Industries (Kima)	Basic Resources	[illegible]	16	12	10	10	71.125	MGWL
6	ELSWEDY ELECTRIC	Basic Resources	[illegible]	18	12	10	10	75.41666667	ACCPT
7	Ezz Steel	Basic Resources	18.125	14	12	10	10	64.125	SM
8	Kafr El Zayat Pesticides & Chemicals Co.	Basic Resources	[illegible]	17	12	10	10	74.6875	MGWL
9	Misr Fertilizers Production Company Mopco	Basic Resources	[illegible]	18	12	10	10	88.8125	GD
10	Misr National Steel - Ataqa	Basic Resources	[illegible]	16	12	10	10	79	ACCPT
11	Paint & Chemicals Industries (PACH)	Basic Resources	[illegible]	17	12	10	10	76	ACCPT
12	Sidi Kerir Petrochemicals (SKPC)	Basic Resources	[illegible]	18	12	10	10	89.375	GD
13	Al Ezz Ceramic & Porcelain (ECAP)	Building Material	[illegible]	17	12	10	10	71.95833333	MGWL
14	Arabian Cement Co SAE (ARCC)	Building Material	[illegible]	18	12	10	10	78	MGWL
15	Ceramic & Porcelain (PRCL)	Building Material	10.75	14	10	10	10	54.75	SS
16	Lecico Egypt (LCSW)	Building Material	[illegible]	13	12	10	10	71.25	MGWL
17	Misr Cement Co ESC (MCQE)	Building Material	[illegible]	16	12	10	10	70.625	MGWL
18	The Arab Ceramic Ceramica Remas	Building Material	[illegible]	13	12	10	10	69.125	MGWL
19	Alexandria Spinning & Weaving (SPIN)	Contracting & Construction engineering	[illegible]	17	12	10	10	81.25	ACCPT
20	Giza General Contracting	Contracting & Construction engineering	[illegible]	16	12	10	10	75.625	MGWL
21	Nasr Company for Civil Works	Contracting & Construction engineering	[illegible]	13	12	10	10	80.125	ACCPT
22	Orascom Construction Ltd (ORASDSCW)	Contracting & Construction engineering	[illegible]	17	12	10	10	75.625	MGWL
23	Alexandria Mineral Oils Company (AMOC)	Energy & Support	[illegible]	18	12	10	10	89	GD
24	AJWA for Food Industries company Egypt	Food , Beverages and Tobacco	[illegible]	12	11	10	10	70.625	MGWL
25	l Khair River For Development Agricultural Investment&Env	Food , Beverages and Tobacco	[illegible]	16	12	10	10	72	MGWL
26	Cairo Poultry (POUL)	Food , Beverages and Tobacco	[illegible]	17	12	10	10	78.77083333	ACCPT
27	Delta Sugar	Food , Beverages and Tobacco	[illegible]	16	12	10	10	81.29166667	ACCPT

Figure 18

integration score sheet

source by author

11.2- Effectiveness and efficiency of the Automated Expert Systems in Credit Analysis.

1. **Timing:** Time is an important factor for measuring efficiency. The final results of the research were that time is divided into two parts: first, the time taken to collect data, and second, the time taken to analyze and reach a conclusion.

A- **Time of data collecting:** After entering the research sample through Microsoft Form, Microsoft performs the average entry time for each company in the sample and shows the time that the tool calculated is 108 Minutes and 21 second per company.

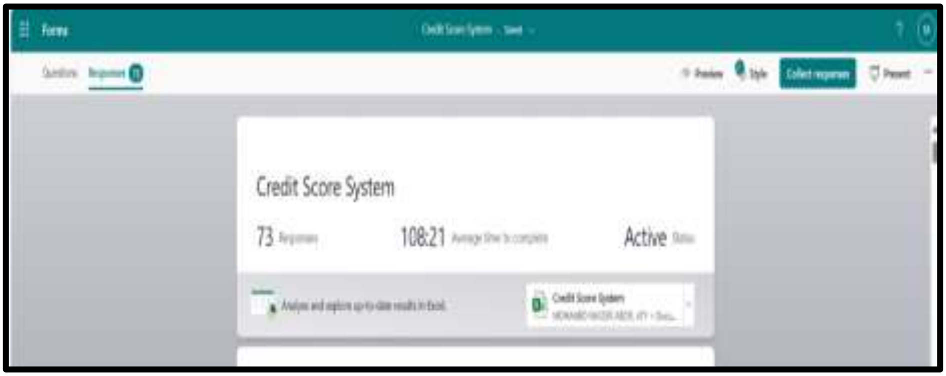


Figure 18
time of data collecting
source by author

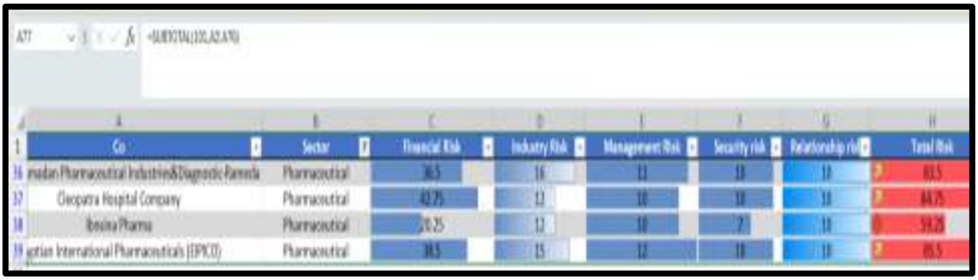
B-**Time of analysis:** Once the data is entered into Excel by transferring it from the collection file, the results and analyzes appear in less than one second.

2. **Accuracy:** Because it is difficult for a bank to give you an evaluation method or customer data by confidentiality and privacy policy, and because we wanted to compare the system’s outputs with the bank’s system outputs, but the researcher compared the results of the system with the results of the initial manual that he applied to some companies to consider the possibility of application, which is what was mentioned in The third chapter is in the testing part, where the results showed complete matching between the manual system

and the expert systems at a rate exceeding 99%. The following figures will show the extent of matching and accuracy.

	company name	company sector	Financial scor	Business/Industry sco	Management sco	Security scor	Relationship sco	total score
71	adan Pharmaceutical Industries&Diagn	Pharmaceutical	36.5	16	11	10	10	83.5
72	Cleopatra Hospital Company	Pharmaceutical	42.75	12	10	10	10	84.75
73	(EIPICO)	Pharmaceutical	38.5	15	12	10	10	85.5
74	Ibnsina Pharma	Pharmaceutical	20.25	12	10	7	10	59.25

Figure 19
manual pharmaceutical credit score
source by author



	Co	Sector	Financial Risk	Industry Risk	Management Risk	Security risk	Relationship ri	Total Risk
36	madan Pharmaceutical Industries&Diagnostic Rameda	Pharmaceutical	36.5	16	11	10	10	83.5
37	Cleopatra Hospital Company	Pharmaceutical	42.75	12	10	10	10	84.75
38	Ibnsina Pharma	Pharmaceutical	20.25	12	10	7	10	59.25
39	ptian International Pharmaceuticals (EIPICO)	Pharmaceutical	38.5	15	12	10	10	85.5

Figure 20
pharmaceutical credit score expert systems
source by author

3.

4. **Reducing the rate of errors in the data entry process:** The data entry process is considered one of the most important processes in credit analysis because on this basis the analysis is done and the result is given. The larger the size of the data entered, the greater the probability of entry error, but through the Microsoft Form tool, it reduces the size of errors that can occur. In the entry process, this is done by separating all the required data into a question for each one separately, and flexibility in the process if the question is closed or an open question.

Figure 22
example of open questions *author* **source by author**

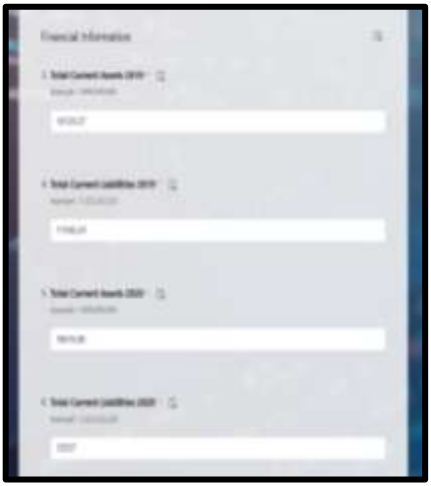


Figure 21
example of closed questions *source by*

5. **Adaptability:** The study emphasizes the importance of having a system that is flexible and adaptable. It should allow for changes and adjustments while keeping the data inputs and

results consistent financial institutions should consider using systems that have this type of flexibility so that they can easily adapt to new regulations or propose new proposals for regulators to evaluate and validate within their testing environment in advance. or changes in evaluation criteria over time, by detailing the equations and creating a rule for each equation, a rule can be applied for each industrial sector, for example, or an equation, which allows flexibility in the creditworthiness analysis process.

6. **The possibility of classifying data and results into more than one classification:** Through the process of dividing the data and results, the data and results can be classified to provide information that helps us support the decision. After the entry process, the data can be classified, for example, in terms of sales volume, capital size, and other data, as well as the results. Companies can also be classified in terms of sectors as well as in terms of points.

Figure 23

classifying by top and bottom companies in each sector

source by author

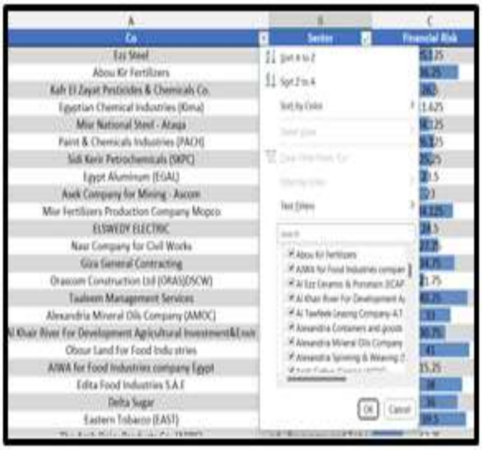


Figure 24

classifying by top and bottom companies overall

source by author

Figure 25

classifying companies by each credit total score

source by author

Figure 26

ıssifying by avg credit scores for highest/lowest grades

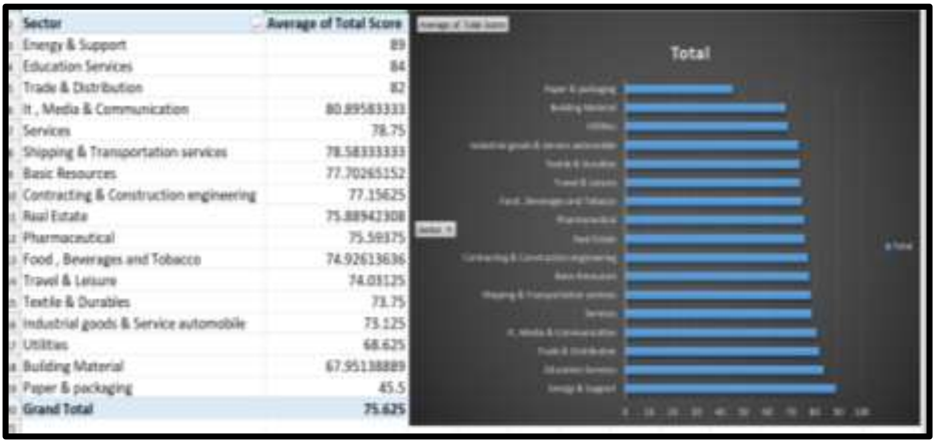
source by author

In addition to the above, the results can be classified according to multiple classifications. For example, the results can be classified according to the sector and then compare the companies within this sector in terms of total score. This represents a very important point and is the ease of comparison to support the decision.

12- Observation:

12.1- database: From an analysis perspective, the larger the sample of companies, the easier the results will be in the comparison process, and the more the system will provide results that increase the opportunity to support the decision

12.2- data analysis and data mining: Based on the above, by increasing the database as well as increasing the requirements, the more it contributes to the process of classifying the results and finding new relationships between the variables, which helps in the process of comparison and analysis to reach sound decisions. For example, the figure (23) shows that after analyzing the data, the system classified the results according to the sector. A comparison was made to the average of each sector separately



Sector	Average of Total Score
Energy & Support	89
Education Services	84
Trade & Distribution	82
It , Media & Communication	80.89583333
Services	78.75
Shipping & Transportation services	78.58333333
Basic Resources	77.70265152
Contracting & Construction engineering	77.15625
Real Estate	75.88942308
Pharmaceutical	75.59375
Food , Beverages and Tobacco	74.92613636
Travel & Leisure	74.03125
Textile & Durables	73.75
Industrial goods & Service automobile	73.125
Utilities	68.625
Building Material	67.95138889
Paper & packaging	45.5
Grand Total	75.625

Figure 27
Data Analyz sectors average
source by author

The analysis also allows for application to data and not just the results. For example, the figure 27 shows the average cash conversion cycle for each sector separately, with an average of four years.

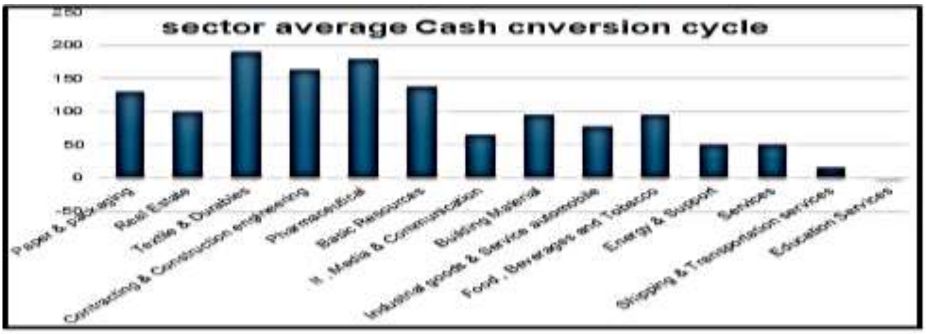


Figure 28
CCC for 'sectors average
source by author

This is not only limited to industry averages, but the position of companies within each industrial sector can be analyzed and compared

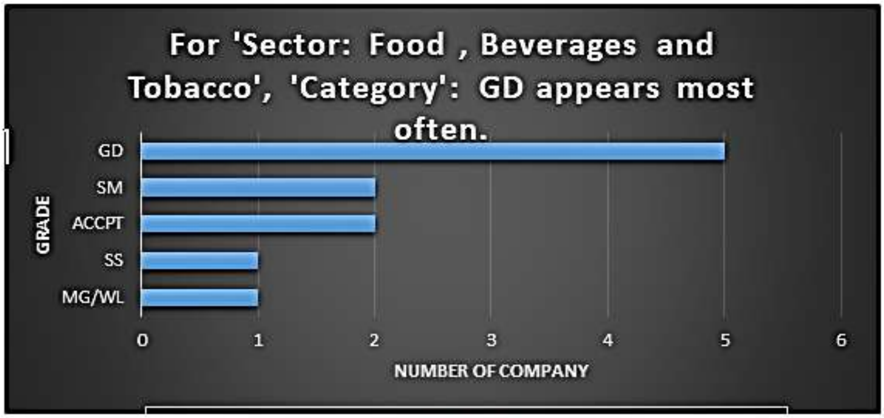


Figure 29
grades of Food , Beverages and Tobacco 'sector
source by author

13- Findings and Results:

13.1- Transformation of Credit Score Model into an Automated Expert Systems

Turning the credit scoring model into an automated expert systems has significantly improved the accuracy, efficiency, and reliability of risk assessment. As noted by **(Tangsawasdirat 2021),** who developed credit scoring models for small and medium-sized enterprises (SMEs) using both financial and non-financial data, our system uses dynamic formulas to automatically assign risk categories (MG/WL, GD, ACCP) based on a company’s overall risk score. This ensures more consistent and unbiased risk classification, providing decision-makers with clearer insights into a company’s creditworthiness.

Similarly, **(Odejide et al. 2024)** highlighted how AI enhances decision-making and risk assessment. Our system aligns with this trend, demonstrating that automation can outperform traditional methods in risk management.

13.2- Effectiveness and Efficiency of the Automated Expert Systems

A comparison between the manual and automated systems shows a 99% match in accuracy, reinforcing the reliability of AI and machine learning in financial settings. This is consistent with **(Myachin, et. al., 2021),** who studied fuzzy expert systems for financial security assessments. Additionally, our system's ability to classify companies in real-time aligns with the research by **(Cavusoglu, et. al., 2023),** who found that Neuro-Fuzzy models successfully classify creditworthiness by combining human expertise with institutional policies.

13.3- Error Reduction in Data Entry

Using Microsoft Forms for data entry minimizes human error by simplifying the process. This reflects **(Teles, 2020)** findings that decision support systems, through machine learning, enhance credit risk evaluation accuracy by reducing manual input errors.

13.4- Adaptability and Classification Capabilities

Our system is adaptable to various industries and sectors, echoing the work of **(Achou 2008),** who emphasized the importance of risk models being flexible and valid across different institutions. By applying custom rules based on specific industry risks, the system remains responsive to changing market conditions. This adaptability supports **(Frederiksust's ,2001)** findings that variables like liquidity, profitability, and solvency are vital in predicting corporate failure.

The system's ability to compare companies within their sectors based on average credit scores and other factors is in line with **(Saygili et al. 2019),** who demonstrated that both financial and non-financial factors, such as liquidity ratios and firm age, play an important role in determining the creditworthiness of SMEs. Our system provides sector-specific analyses and detailed company classifications, reflecting this approach.

14- Recommendations

14.1- Implementation of Automated Expert Systems: Given the effectiveness and efficiency demonstrated by the automated expert systems in credit analysis, it is recommended that financial institutions consider adopting similar systems to enhance the accuracy and speed of their credit scoring processes.

14.2- Emphasize Data Collection Efficiency: To streamline the data collection process, utilizing tools like Microsoft Form can significantly reduce the time and potential errors associated with manual data entry. Encouraging the use of such tools can improve efficiency and data accuracy in credit analysis procedures.

14.3- When comparing the results of the automated expert systems with manual evaluations, it's essential to keep customer data confidential and private. Institutions need to handle any data used for these comparisons very carefully, making sure they follow all the necessary rules and regulations to protect privacy.

14.4- The study emphasizes the importance of having a system that is flexible and adaptable. It should allow for changes and adjustments while keeping the data inputs and results consistent. Financial institutions should think about using systems that have this kind of flexibility, so they can easily adapt to new regulations or changes in evaluation criteria over time.

14.5- Enhanced Decision Support: Leveraging the capability of the system to classify data and results into multiple categories can provide valuable insights to support decision-making processes. Institutions should explore ways to utilize these classification features to gain deeper insights into customer profiles, sector performance, and overall risk assessment.

15- Conclusion

The transformation of a credit score model into an automated expert systems presents significant advancements in the field of credit analysis. The findings of this study underscore the effectiveness and efficiency of such systems in streamlining the credit evaluation process, reducing errors, and enhancing decision-making capabilities. The demonstrated accuracy, flexibility, and data classification features of the system provide valuable insights for financial institutions seeking to optimize their credit scoring procedures. By embracing automated expert systems, institutions can not only improve the speed and accuracy of credit analysis but also adapt more effectively to changing regulatory environments and customer needs. Overall, this study highlights the potential of automated expert systems to revolutionize credit analysis practices and pave the way for more informed lending decisions in the future.

16- Limitation and Future studies

16.1- Research limitations

A major limitation is the geographical scope, as the study was conducted exclusively in Egypt, focusing on companies listed on the Egyptian Stock Exchange (EGX 100). This means that the findings are shaped by the economic and regulatory environment in Egypt, which may limit their applicability to other markets with different financial systems. Additionally, the sample size included 71 companies from the non-financial, providing a diverse representation of industries but excluding financial institutions, which play a critical role in assessing credit risk. This omission limits insights into how credit risk factors operate in the financial sector.

The study's time frame (2019-2022) is another limitation, as it may not fully capture long-term economic cycles or structural shifts in credit risk dynamics beyond this period. Furthermore, the research focused on five primary credit risk factors – financial, industry, governance, security, and relationship risks – while macroeconomic conditions, geopolitical risks, or technological disruptions were not explicitly analyzed. Finally, while the model aims to be generalizable to non-financial sectors, it may not fully consider sector-specific differences in business cycles, regulatory policies, or competitive pressures, which may impact its applicability across different industries.

16.2- Future Studies

Based on these limitations, future research could explore several key areas. One potential direction is to evaluate the performance of automated expert systems across different types of firms, such as small and medium-sized enterprises, to assess their effectiveness in diverse industries and identify sector-specific challenges or benefits. Additionally, improving the credit risk model by incorporating new factors or alternative credit analysis models could enhance the accuracy and efficiency of credit assessments.

Further studies could also examine the role of automated expert systems in other financial areas, including investment portfolio analysis and financial forecasting, to assess their broader impact on financial decision-making. Finally, an important avenue for research is to analyze the impact of automation on jobs in the financial sector, particularly the skills required for future professionals as financial institutions move toward AI-driven systems.

By addressing these limitations and expanding research into these future areas, scholars and practitioners can continue to develop expert credit scoring systems, ensuring greater adaptability, accuracy, and efficiency in financial risk assessment.

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