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The Impact of Big Data Analytics Using Artificial Intelligence on Financial Risk Management: An Applied Study on the National Popular Credit Bank (CPA) Using Structural Equation Modeling Technique (SEM-PLS)

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Abstract:

This research aims to explore the impact of big data analytics using artificial intelligence in its four dimensions (expert systems, machine learning, neural networks, and intelligent agents) on the effectiveness of financial risk management. To achieve this goal, a case study was conducted on the National Popular Credit Bank (CPA), where data were collected through a questionnaire directed at a sample of 55 employees, and analyzed using the Structural Equation Modeling methodology (SEM-PLS) to provide practical evidence of the nature of this relationship in the CPA.

The research found a strong positive impact of the combined dimensions of artificial intelligence on financial risk management, explaining 68.6% of the variance in the dependent variable (R^2=0.686). The results revealed a variation in the importance of these dimensions; the analysis showed a statistically significant effect of machine learning and intelligent agents, while no effect was found for expert systems and neural networks. These results highlight the strategic importance of predictive and automated technologies in enhancing risk management in the banking sector.

Keywords: Big Data Analytics; Artificial Intelligence; Financial Risk Management; Structural Equation Modeling (SEM-PLS); Algerian Banking Sector.
JEL Classification : C55; C63; G32; G21; O33.

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1. Introduction:

The financial sector has entered a phase of structural turbulence driven by accelerating digital innovation and a shift in risk dynamics. In this context, AI-enabled big data analytics emerges as a lever capable of reshaping decision-making systems and risk management within banks. However, converting this technological promise into tangible operational impact requires an epistemological review of historical assumptions (extrapolating the future from the past and assuming approximate normality), and a distinction between risk attribution and its operationalization amid data abundance, reliance on external knowledge sources, and advances in algorithms finance.

The study proceeds from a central hypothesis that integrating big data analytics and artificial intelligence enhances the effectiveness of risk management by improving accuracy, shortening early-warning lead times, aligning capital with exposure levels, and strengthening compliance. Yet automation alone is insufficient without governance, decision criteria, and organizational design that enable integration into operations. Accordingly, we propose a conceptual framework linking data and analytics capabilities (data quality, analytical architecture, model maturity, analytical human capital) to risk outcomes (estimation accuracy, default prediction, exposure control, response speed, regulatory compliance), while testing the mediating role of governance/standardization and the moderating roles of reliance on external data and the intensity of environmental turbulence.

National Popular Credit (CPA) provides a suitable applied setting given the nature of its operations, the diversity of its activities, and its position in a market whose digitization is accelerating. Accordingly, the study estimates the direct and indirect effects of analytics and AI capabilities on the effectiveness of risk management within the bank, and examines the predictive validity of the proposed model in an actual banking environment

1.1 Problem Statement.

Based on the above, the research problem can be formulated in the following main research question:

What is the impact of big data analytics using artificial intelligence dimensions (expert systems, machine learning, neural networks, intelligent agents) in enhancing the effectiveness of financial risk management at the National Popular Credit Bank (CPA)?

1.2 Conceptual Model of the Research, Variables, Hypotheses:

Based on the theoretical framework of the study and its research questions, the following main hypothesis and sub-hypotheses were formulated to be tested statistically:

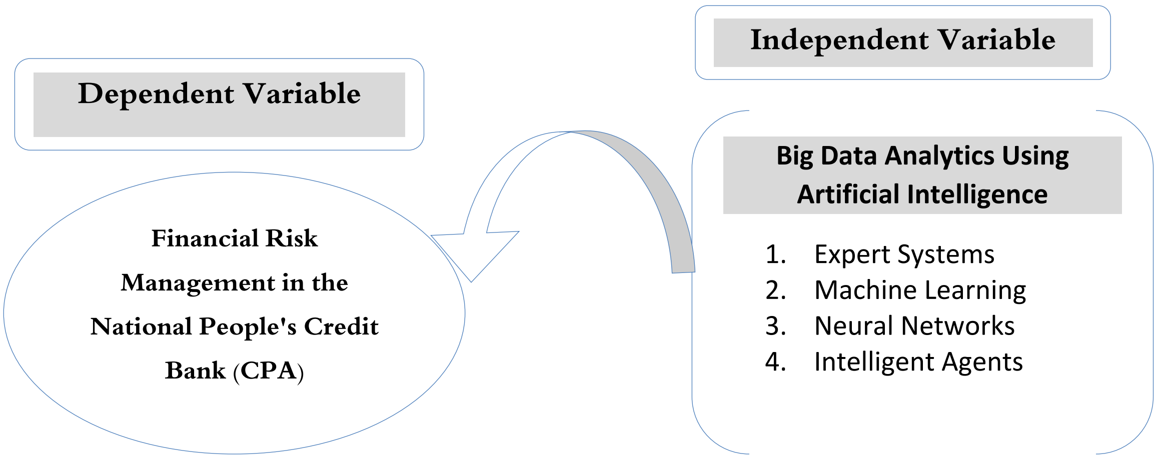
1.2.1 Main Hypothesis:

There is a statistically significant positive impact of big data analytics using artificial intelligence as a whole on financial risk management.

1.2.2 Sub-Hypotheses:

- There is a statistically significant positive impact of using expert systems on financial risk management.
- There is a statistically significant positive impact of using machine learning on financial risk management.
- There is a statistically significant positive impact of using neural networks on financial risk management.
- There is a statistically significant positive impact of using intelligent agents on financial risk management.

Figure N° 01: Illustrates the hypothetical model of the research



Source: Prepared by the researchers

2. Theoretical Framework of the Research

2.1 Overview of Big Data Analytics

One of the emerging buzzwords in the IT industry, such as large data analytics based on artificial intelligence, has implications in the engineering industry, an increasingly popular field for many companies. Specifically, big data analytics is the process of analyzing large and/or complex data sets to provide overall or user- or domain-centric knowledge to draw a conclusion about the information they contain (mostly dimensions that were too complex, varied too quickly, or too large to be processed by standard tools). In finance, methods such as descriptive analytics, predictive analytics, and prescriptive analytics can be used with traditional accounting data, along with other big, dark, and alternative data such as text, image, video, audio, or sensory data, to draw a portfolio of loans. Warranties, exchanges, asset evaluations, fraud detection, business quality scoring, and debt settlement compliance insights are important in the decision-making process about the loan. In order to be able to perform big data analysis in the world, benchmarks have been developed in the field of finance, although data collection, storage, and analysis must be carried out according to this application. The real-time analysis allows the company to take immediate action, while the prediction allows future actions to be taken, and the pre-embargo strategy allows action-taking considering the future commercial implications**.** (Wang, Xiuping, & Zhang, 2021)

2.2 Overview of Artificial Intelligence

AI can be defined as a set of theories and techniques for generating artificial systems accomplished by computer software. AI techniques are able to mimic human cognitive functionality in order to generate some form of output. They are based on three fundamental techniques: machine learning, natural language processing, and computer vision. Machine learning is a specific framework in the AI community and is used when the human programmer cannot write an algorithm due to the large number of variables and decision-making criteria. It is a self-adaptive algorithm that keeps improving its functionalities when it receives more data. AI is efficient in analyzing what a human is able to pick up within the data in a single moment, inferring it from a series of historical data, and predicting the effect on the future. Consequently, it can help banks and insurance companies prevent losses**.** (Hassan, Aziz, & Andriansyah, 2023)

AI is a useful tool in this kind of task, and it is employed in different applications in the field of financial risk management: credit risks or rating assessment, operational risks often linked to the concentration risk on real estate assets in the event of a crisis, liquidity, stock market risks, money laundering activities, backlogs, and errors. Now, since data has been becoming too much and too diversified, AI tools have been updating themselves, making them more efficient and accurate. Access to data is cheaper and easier than before, and AI technologies, which include machine learning techniques, are improving. (Bello, 2023)

2.3. Benefits of Using Big Data Analytics and Artificial Intelligence in Financial Risk Management

The ever-increasing digitalization brings about huge batches of data, which are too massive for human personnel to process, rendering the potential information contained within the dataset largely untapped by its operator. That is one of the reasons why financial services firms have been increasingly turning towards the aid of technologies of big data analytics using artificial intelligence. As a result, the volume, velocity, variety, and veracity of data are to be taken into consideration (Mariani & Wamba, 2020)

The utilization of big data analytics and artificial intelligence delivers added value in numerous aspects, which include, for example: improved accuracy of risk identification, assessing and mitigating while allowing faster decision-making processes; the opportunity to replace manual intervention with automation, which generally improves costs; potential positive impact on the reduction of operational risks; and the capability of better predicting potential issues. Moreover, a more transparent and fairer allocation of resources is available. This very context of empowered and analytical customers implies engagement in business processes, which is impossible to achieve without getting insights from customer data. (Agbehadji, Awuzie, Ngowi, & Millham, 2020)

3. Applied Framework of the Research

Based on the theoretical framework that established the study's concepts, this part aims to translate the hypothetical model into a measurable practical reality. This section will present the methodology and the field procedures followed step by step, starting from the procedures of data collection and sample identification, through assessing the quality of the measurement tool, and ending with the analysis of results and testing of hypotheses using Structural Equation Modeling (SEM-PLS).

3.1 Method and Methodological Procedures

3.1.1 Data Collection and Sample:

To obtain the data necessary to test the study's hypotheses, data were collected from a sample of employees of the National Popular Credit Bank (CPA). A purposive sampling method was adopted, targeting employees with experience and direct knowledge in the fields of risk management, data analysis, and information technology, in order to ensure accurate responses that align with the research objectives. The study tool was distributed in both paper and electronic formats to increase the response rate. After the data collection and sorting period ended, the final sample size valid for statistical analysis was 55 questionnaires.

3.1.2 Description of the Data Collection Tool:

A questionnaire specifically designed to measure the study variables was used. The questionnaire was divided into three main parts:

- **Part One:** Dedicated to demographic information of the respondents (job title, years of service).
- **Part Two:** Included 16 statements to measure the independent variable with its four dimensions (expert systems, machine learning, neural networks, and intelligent agents).
- **Part Three:** Covered the dependent variable (financial risk management) through 7 statements.

All statements related to the study variables were measured using a five-point Likert scale, ranging from (1) "Strongly Disagree" to (5) "Strongly Agree". The sample members were asked to rate their agreement with each statement, and their opinions will be analyzed as shown in the table No. (01).

To ensure the quality of the measurement tool and its ability to collect accurate and reliable data before distributing it to the final sample, the following tests were conducted:

- **Validity:** To verify content validity, the preliminary version of the questionnaire was presented to a group of specialized referees from academics and professionals in the banking field. Their observations were taken into account, and some statements were modified to ensure clarity and their ability to measure what they were designed for.
- **Reliability:** To measure the stability of the questionnaire results if redistributed more than once under the same conditions, a pilot study was conducted on a sample of 20 individuals from outside the main research sample. After analyzing the data, the overall Cronbach's Alpha coefficient value was 0.823. This value is considered very high and indicates an excellent degree of reliability for the tool, as the statistically acceptable value is 0.70 or more**.** (Hair, Hult, Ringle, & Sarstedt, 2022)

3.1.3 Data Examination and Distribution Type Identification:

After verifying the reliability and validity of the questionnaire, the data collected from the main sample (55 individuals) were examined. Data examination and determining the nature of their distribution is a fundamental step in statistical analysis, as it helps in selecting the appropriate statistical tests (parametric or non-parametric) and achieving reliable results. The data collected from the main sample were examined to verify their distribution nature using the Kolmogorov-Smirnov test. (Osama Rabie, 2008, p. 115)**.** The table No. (02) displayed the findings.

The results of the Kolmogorov-Smirnov test showed that the data distribution for both the independent and dependent variables does not follow the normal distribution, as the p-value (P-value = 0.000) was less than the significance level (0.05). This result confirms that the data do not meet the conditions of parametric tests, which necessitates the use of non-parametric statistical methods in data analysis. Therefore, Partial Least Squares Structural Equation Modeling (SEM-PLS) was selected as the appropriate methodology for evaluating the study model and testing its hypotheses, as this method does not require normal data distribution (Hair, Hult, Ringle, & Sarstedt, 2022, p28), and it is highly suitable for small to medium sample sizes (Hair, Hult, Ringle, & Sarstedt, 2022, p. 24), which enhances the accuracy and reliability of the results.

In addition, descriptive statistical methods such as measures of central tendency (arithmetic mean) and measures of dispersion (standard deviation and coefficient of variation CV) were used to describe the respondents' opinions. The statistical programs used in the study include **SPSS V.29**. In addition, the program (**SMART PLS V.4)** was used, which specializes in implementing SEM-PLS techniques for analyzing the structural model and testing the hypotheses.

3.2 Results Analysis and Hypothèses Testing:

In this section, the data collected from the study sample will be presented and analyzed using the statistical methods previously identified, with the aim of answering the study questions and testing its hypotheses. The analysis will be divided into two parts: descriptive analysis, then model analysis and hypothesis testing using Structural Equation Modeling (SEM-PLS).

3.2.1 Descriptive Analysis of the Questionnaire Data:

A. Characteristics of the Study Sample:

The results of the demographic characteristics analysis of the study sample (N=55) showed that the majority were male (58.2%). The largest age group was between 30 and 39 years (38.2%), which aligns with the data on professional experience, where the vast majority (63.6%) had between 5 and 10 years of experience. This indicates that the sample consists of professionals in a mature career stage. In terms of educational qualification, the sample is characterized by a high level of education, as all members hold at least a university degree (67.3%), with a significant proportion

(32.7%) holding postgraduate degrees. Regarding job roles, data analysts represented a core segment (40.0%), which directly serves the study's objectives, while the largest proportion (54.5%) fell under various other job roles within the bank (CPA).

B. Analysis of Respondents' Opinions and Attitudes Toward Research Variables:

Through table No. (03), showing the descriptive analysis results of the study sample's opinions, where a generally positive and high trend toward all research variables is evident. The overall arithmetic mean for the independent variable "Artificial Intelligence Dimensions" was (3.6705), and for the dependent variable "Financial Risk Management" (3.7247), both falling under the "High" evaluation category. This reflects a strong perception among employees of the importance and role of these technologies in the bank.

When detailing the dimensions of the independent variable, the dimension "Expert Systems" ranked first with an arithmetic mean of (3.7727), indicating it is the most applied or recognized by the sample, followed directly by the dimension "Machine Learning" with a mean of (3.7136).

Regarding opinion consistency, the coefficient of variation (CV) indicates that the dimension "Machine Learning" recorded the lowest dispersion rate (10.48%), signifying a high level of agreement among the sample members regarding its importance. On the other hand, the "Expert Systems" dimension showed the highest dispersion rate (15.53%), which may reflect variation in the level of knowledge or actual application within the bank.

The above results show that the National Popular Credit Bank (CPA), from the perspective of its field sample, places high importance on both the application of artificial intelligence technologies and the effectiveness of financial risk management. This high and closely aligned perception between the two variables provides a solid and logical foundation to move on to the next part of the analysis, which aims to go beyond mere description toward measuring the nature and strength of the causal relationship between them through building and testing the study's structural model.

3.2.2 Evaluation of the Research Model and Hypotheses Testing Using SEM-PLS Modeling:

After reviewing the descriptive aspect, this section represents the core of the inferential analysis of the study, where the methodology of Structural Equation Modeling (PLS-SEM) via the program (Smart PLS V.4) will be used to evaluate the hypothetical model. According to (Hair, Hult, Ringle, & Sarstedt, 2022), this approach requires following a two-stage integrated analysis. The first stage concerns the evaluation of the measurement model's quality (validity and reliability of the tool), followed by the second stage, which involves evaluating the structural model and testing the research hypotheses.

A. First Stage: Evaluation of the Measurement Model Using SEM-PLS

Initially, the measurement model for each of the study variables (economic intelligence, corporate governance, and corporate performance) will be evaluated to ensure measurement quality and verify convergent validity, discriminant validity, and reliability.

B. Second Stage: Evaluation of the Structural Model and Hypotheses Testing

involves: ensuring the absence of multicollinearity between the independent variables through examining the VIF values; assessing the model's explanatory power through the coefficient of determination (R^2) and the effect size (f^2) of each independent variable; verifying the model's predictive relevance using the Q^2 value; and finally, examining the path coefficients (β) and their statistical significance (p-value ≤ 0.05) to confirm the validity of the hypotheses and the relationships between the variables.

Through these two stages, we are able to construct a comprehensive research model capable of accurately and reliably explaining the impact of artificial intelligence dimensions in big data analytics on financial risk management. While the first stage ensures the accuracy of measurement, the second stage reveals the strength and direction of causal relationships between the variables, providing an accurate statistical answer to the research problem and its hypotheses.

3.3 Results of the Measurement Model Assessment :

The assessment of the measurement models includes the following steps according to (SEM-PLS) modeling. as illustrated in figure No. (02).

The table No. (06) shows the results of the measurement model assessment for the latent variables in the model, in order to verify the quality of the measures in terms of reliability and convergent validity:

3.1.1 Reliability Analysis:

Reliability is defined as “the extent to which a measure is consistent and produces stable results under similar conditions.” (Hair, Hult, Ringle, & Sarstedt, 2022, pp. 118 , 119). Simply put, if we repeat the measurement process several times, will we obtain approximately the same results? If the answer is yes, then the measure is reliable.

The results show excellent levels of reliability for most variables. The values of Cronbach’s Alpha and Composite Reliability (CR) exceeded the

0.70 threshold for all dimensions except for the "Machine Learning" dimension, which recorded a Cronbach's Alpha value of (0.639), below the acceptable minimum. However, the Composite Reliability value for this dimension (0.791) remains within the acceptable range.

3.3.2 Convergent Validity Analysis:

This refers to "the extent to which indicators (items) that represent the same construct actually converge and share a high proportion of variance, confirming that they effectively measure the same construct" (Hair, Hult, Ringle, & Sarstedt, 2022, p. 120)**.** It is assessed using two main criteria:

A. Indicator Reliability:

Measured through the outer loadings for each indicator, which are recommended to be greater than 0.708 (or 0.70 as a practically accepted rule (Hair, Hult, Ringle, & Sarstedt, 2022, p. 117)**.**

B. Average Variance Extracted (AVE):

This is a construct-level measure, and its value should exceed 0.50 to ensure that the construct explains more than half of the variance in its indicators (Hair, Hult, Ringle, & Sarstedt, 2022, p. 120). From the table we find:

- **Indicator Reliability:** By examining the outer loadings, it is observed that most statements (indicators) contribute significantly to measuring their respective variables, as their loadings exceeded the 0.70 threshold. Except for some indicators that recorded lower loadings, most notably statement No. 06 (0.449) and statement No. 07 (0.618) within the "Machine Learning" dimension, and statement No. 20 (0.561) within "Financial Risk Management." These statements with low loadings will be retained and not removed from the model since their deletion did not lead to a substantial improvement in the values of Composite Reliability (CR) or Average Variance Extracted (AVE) for the other dimensions.
- **Average Variance Extracted (AVE):** The AVE values for all variables exceeded the 0.50 threshold, confirming the presence of convergent validity at the variable level. This means that each variable explains more than 50% of the variance in its indicators, which is evidence that the indicators of each variable indeed converge to measure the same latent construct.

In general, the measurement model possesses good psychometric properties, which justifies the quality of the tool used (the questionnaire). These results enhance confidence that the variables were measured accurately and reliably, paving the way for the evaluation of Discriminant Validity to ensure that each variable is distinct and independent from the other variables in the model.

C. Discriminant Validity Assessment:

After confirming the convergent validity of the model, the next step is the assessment of discriminant validity to ensure that the variables in the model are distinct from one another, such that each measures a different concept. While there are multiple criteria such as the Fornell-Larcker criterion and cross-loadings, this research will rely on the Heterotrait-Monotrait Ratio (HTMT) criterion. The HTMT criterion is considered an advanced and more effective and accurate method for detecting discriminant validity issues compared to traditional criteria (Henseler, Ringle, & Sarstedt, 2015). The acceptable threshold is that HTMT values should be less than 0.90, and the results are recorded in the table No. (07).

We note from the table No. (07), that most of the bivariate correlation values between the variables fall within the acceptable range, not exceeding the recommended threshold (0.90), which generally supports the discriminant validity of the model.

Conclusion of the First Stage (Measurement Model Assessment): The model variables demonstrate good validity and reliability. To complete this analysis, we will proceed with the evaluation of the structural model.

3.4 Results of Structural Model Assessment and Hypothesis Testing

After ensuring that the measurement model possesses the necessary validity and reliability properties, we move in this stage to evaluate the structural model. This stage aims to test the hypotheses set for the research by examining the strength and direction of relationships between variables, in addition to assessing the explanatory and predictive power of the model. This stage includes a series of steps:

3.4.1 Collinearity Assessment (VIF):

Before examining the path coefficients, it was verified that there is no collinearity problem among the independent variables (dimensions of artificial intelligence) when explaining the dependent variable (financial risk management). The table No. (08), shows the Variance Inflation Factor (VIF) values for each independent variable

It is clear from the table No. (08), that all VIF values came less than the threshold (5). According to (Hair, Hult, Ringle, & Sarstedt, 2022, p. 191), VIF values exceeding 5 indicate a critical collinearity problem. Accordingly, it can be concluded that there is no critical collinearity problem among the independent variables, which allows reliance on the results of the path coefficient estimates with confidence.

3.4.2 Model Quality Evaluation through R^2 (Explanatory Power), f^2 Effect Size, Q^2 Predictive Relevance, and SRMR Fit Index

Through table No. (09), showing that the model possesses high quality, for the following reasons:

- **Explanatory Power (R^2):** The coefficient of determination reached 0.686, which means that the dimensions of artificial intelligence collectively explain 68.6% of the changes (variance) occurring in the variable of financial risk management. According to the standards of (Chin, 1998), which consider that an R^2 value equal to or greater than 0.67 is strong, the model has excellent explanatory power.
- **Predictive Relevance (Q^2):** The Q^2 value reached = 0.452, which is significantly greater than zero, indicating that the model has good predictive relevance. (Hair, Hult, Ringle, & Sarstedt, 2022, p. 197)
- **Overall Model Fit (SRMR):** This index value was 0.077, which is less than the recommended threshold (0.08), indicating a good fit between the proposed model and the field data. (Hair, Hult, Ringle, & Sarstedt, 2022, p. 198)

In general, it can be concluded that the proposed structural model possesses high quality and significant explanatory power. The R^2 value, which reached 0.686, is classified as "strong," confirming that the dimensions of artificial intelligence collectively are essential and significant variables in explaining a large portion of the changes in financial risk management. Moreover, the positive predictive relevance value (Q^2 = 0.452) and the acceptable overall model fit value (SRMR = 0.077) together reinforce the confidence that the model is not merely a theoretical explanation but also has predictive capability and fits well with the field data. These combined results demonstrate that the current model provides a solid foundation for understanding and explaining the causal relationships between the application of big data analytics using artificial intelligence and the enhancement of financial risk management in the National Popular Credit Bank.

According to the standards of (Cohen, 1988)**,** which are relied upon by (Hair, Hult, Ringle, & Sarstedt, 2022, p. 196)**,** it is clear from the table No. (10) that the dimensions of "Machine Learning" (f^2 = 0.182) and "Intelligent Agents" (f^2 = 0.326) have a medium effect size in explaining the variance in financial risk management. In contrast, the dimensions of "Expert Systems" (f^2 = 0.042) and "Neural Networks" (f^2 = 0.033) have a small effect size. These results highlight the relatively higher importance of the dimensions of machine learning and intelligent agents in the study model.

These results not only support the general hypothesis that artificial intelligence plays an influential role, but also provide a precise strategic insight for the bank’s management. They suggest that advanced predictive capabilities (machine learning) and real-time automated monitoring tools (intelligent agents) are the primary drivers for enhancing risk management, at the expense of traditional rule-based systems (expert systems) or those more complex and difficult to interpret (neural networks). This guides the decision-maker in the bank to focus investments and resources on developing and applying these two specific dimensions to achieve the highest possible return in the area of financial risk management.

And although the effect size (f^2) provides an important indication of the relative importance of each dimension, it is not sufficient alone to prove the validity of the hypotheses. Therefore, the next step is:

3.4.3 Assessment of the Statistical Significance of Path Coefficients in the Structural Model and Hypothesis Testing:

To estimate statistical significance, t-values were relied upon and compared with the critical value (1.96), and p-values were compared with the significance level (0.05), in addition to examining the confidence intervals to ensure they do not include the value zero. The table No. (11) presents a summary of the hypothesis testing results.

A. Analysis of the Main Hypothesis:

The table shows that the relationship between the overall independent variable “Dimensions of Artificial Intelligence” and the dependent variable “Financial Risk Management” is very strong and statistically highly significant. The path coefficient reached ($\beta = 0.828$), and the t-value ($t = 9.153$), which is far above the critical value (1.96), with a p-value ($p = 0.000$) less than (0.05). Also, the confidence interval [0.614, 0.935] does not include zero. Therefore, the main hypothesis of the study is accepted.

- **Interpretation of the result:** This result confirms that the National Popular Credit Bank’s adoption of artificial intelligence technologies in big data analytics significantly and effectively contributes to enhancing the efficiency of financial risk management. This supports the theoretical framework which states that the ability to process and analyze vast amounts of data provides proactive and predictive insights that traditional methods cannot achieve, thereby enhancing the bank’s ability to identify, assess, and respond to risks more efficiently.

4. Discussion of Results and Research Recommendations

4.1 Research Results and Discussion:

The research arrived at a main finding, namely the existence of a strong effect of the dimensions of artificial intelligence on financial risk management, as these dimensions collectively explained 68.6% of the variance in the dependent variable ($R^2 = 0.686$). This supports the main hypothesis of the research. At the level of sub-hypotheses, the analysis revealed a clear variation in the effect of each dimension, as the second and fourth hypotheses were accepted, both of which demonstrated a strong and statistically significant positive effect for the dimensions of “machine learning” ($\beta = 0.563$) and “intelligent agents” ($\beta = 0.506$). In contrast, the first and third hypotheses were rejected due to the lack of statistically significant effect for the dimensions of “expert systems” and “neural networks.”

These results provide deep insights that go beyond merely confirming the overall effect, as they reveal the relative importance of each technology. The strong effect of the “machine learning” and “intelligent agents” dimensions is the most prominent finding. This can be explained by the advanced predictive capabilities provided by machine learning to accurately understand customer behavior and predict any potential fraud before it occurs, along with the real-time monitoring provided by intelligent agents. Together, they represent the true and most impactful added value in the modern banking environment.

In contrast, the lack of a significant effect of expert systems and neural networks raises important questions. This may be due to the fact that expert systems, which rely on fixed rules, have become less capable of keeping pace with changing risks, while the working method of neural networks remains obscure and complex, making it difficult for managers to rely on them in making crucial financial decisions. Therefore, the research not only confirms the importance of artificial intelligence, but also outlines the most effective and practical technologies for managing banking risks.

4.2 Theoretical and Practical Contributions of the Research

The importance of this research goes beyond merely testing hypotheses, as it provides a set of theoretical and practical contributions that can be summarized as follows:

- The study addresses a modern and important topic at the heart of current transformations in the financial sector, namely exploring the impact of AI-supported big data analytics on risk management. This topic is still in its early stages of academic research, especially in the Algerian banking sector.

- The research proved that treating artificial intelligence as a single block may be misleading. By breaking it down into four different dimensions, the results revealed that the effects of these dimensions are not homogeneous, with machine learning and intelligent agents having strong effects, while the other dimensions did not show such effects. This calls on future researchers to adopt a multidimensional model when studying the impact of artificial intelligence.
- This research presented an accurate diagnostic tool for management and decision-makers, highlighting current strengths (benefiting from machine learning and intelligent agents) and areas that need development or reassessment (the role of expert systems and neural networks).
- The research results provided a clear roadmap for decision-makers, guiding management to focus its investments and technical and training resources on the technologies that have proven to have the greatest and most effective impact in enhancing risk management, ensuring maximum return on investment.
- This research provides management with a practical and tangible guide that can be used to justify strategic decisions related to technology adoption to the board of directors and regulatory bodies, instead of relying on general trends or theoretical estimates.

4.2.3 Recommendations:

Based on these results, the following recommendations can be made:

- CPA bank management should focus its investments and technical resources on specifically developing and applying machine learning and intelligent agent technologies, as they have proven to have the greatest practical impact.
- The necessity of designing specialized training programs for risk managers and analysts on how to use and interpret the outputs of predictive models, to enhance confidence in them and integrate them into decision-making processes.

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