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Article

Artificial Intelligence Capability for Enterprise Financial Risk Management and Business Resilience

Nasir Uddin[1], Md Yeasir Arafat[2], Wali Ahmed[3]

1. Master of Science in Analytics and Systems, University of Bridgeport, Bridgeport, CT 06605, USA
2. Master of Science in Analytics and Systems, University of Bridgeport, Bridgeport, CT 06605, USA
3. Department of Computer Science, University of Bridgeport, USA

* Correspondence: nuddin@my.bridgeport.edu

Abstract: Background: Artificial intelligence is now making more and more impact on the enterprise financial risk management process, contributing to better risk assessment, prediction and decision-making processes. At the same time, there is not enough empirical data that would explain how AI can be used to improve the mentioned processes in the context of effective financial risk management and risk response, and in addition to that, how such usage impacts business resilience. Methods: In this study, a quantitative cross-sectional design was used, and online survey was conducted among 175 specialists from the United States. Three factors (AI Risk Assessment Capability, AI Risk Prediction Capability and AI Decision-Making Capability) and three outcomes (Financial Risk Management Effectiveness, Risk Response Agility and Business Resilience) were considered in the proposed framework. Results: Consistently positive correlations were observed for all variables included in the research. Financial Risk Management Effectiveness correlated best with Business Resilience at $r = 0.756$. For Financial Risk Management Effectiveness, the best predictor variable was AI Risk Prediction Capability at $\beta = 0.314$, followed by AI Risk Assessment Capability at $\beta = 0.286$ and AI Decision-Making Capability at $\beta = 0.267$. In turn, Risk Response Agility was best predicted by Financial Risk Management Effectiveness $\beta = 0.582$, and Business Resilience was predicted positively by Risk Response Agility $\beta = 0.438$. The results explained 67.2% of the variance in Business Resilience. Conclusion: The obtained results suggest that risk capabilities of organizations based on AI have the potential to increase the efficiency of financial risk management and build business resilience.

Keywords: Artificial Intelligence, Financial Risk Management, Risk Prediction, Business Resilience, Enterprise Risk Governance

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1. Introduction

The use of artificial intelligence (AI) is drastically changing the framework of enterprise risk management, which facilitates transforming vast and complex volumes of data into financial intelligence for the organizations [1]. Modern enterprises are facing a highly volatile and unpredictable operating environment due to the presence of issues such as market volatility, cyber risks, regulatory pressure, financial frauds, liquidity problems, and fast-changing business environment [2]. It is observed that there are certain shortcomings of the traditional approach to managing financial risks due to the fact that they mostly depended on the historical data, rules, and periodic evaluation [3]. Contrarily, AI-based systems have the ability to constantly analyze data from various sources, detect complex patterns, discover new threats, and help managers in making a decision [4]. Therefore, it can be concluded that AI capability is becoming a very valuable strategic resource for improving the financial risk management and maintaining organizational stability [5]. Using AI for risk assessment allows an organization to analyze a variety of financial factors at once and find possible weaknesses that might be hard to spot via traditional methods of analysis [6]. The ability to forecast risks using trends, real-time data, and complex behavior patterns is also possible due to AI. At the stage of decision-making, the use of AI will help organizations receive necessary analytical insights and make the right choice of actions in situations of uncertainty [7]. All the capabilities mentioned above will help move the process of risk management of enterprises from the predominantly reactive stage to the more proactive and intelligence-based one [8].

It becomes increasingly clear that an essential part of financial resilience of enterprises today is the use of the AI capability. Financial risks can influence many factors related to the functioning of an enterprise and its financial status very fast, such as liquidity, profitability, ability to invest, continuity, and competitiveness in the long term [9]. Therefore, the ability of an organization to react to financial risks quickly and appropriately is of great importance besides the ability to identify them [10]. The increased efficiency in risk identification, prediction, and decision-making can enhance the organization's agility and increase its resilience by allowing it to absorb, adapt, and recover from any financial disturbances through the use of AI [11]. Although there has been wide-ranging use of AI technologies, empirical research is still lacking on their value to organizations. Current literature mainly focuses on individual applications of AI technologies such as fraud detection, credit scoring, forecasting, and automation of compliance [12]. Individual application is limited in revealing AI's role in risk management for enterprises. There is limited empirical research on the impact of multiple AI capabilities on financial risk management effectiveness, agility of risk response, and business resilience [13]. It is vital to understand that adoption of technology itself does not guarantee any improvement in the organization's performance. The integration of AI capabilities in risk management processes will determine if the investment in AI leads to improved resilience [14].

In light of these issues, this study proposes an integrated empirical model that explores the relationships between AI Risk Assessment Capability, AI Risk Prediction Capability, and AI Decision-Making Capability with Financial Risk Management Effectiveness, Risk Response Agility, and Business Resilience. The data used in the study was collected using an online survey from 175 professionals in the US. The study is intended to examine these relationships concurrently for a more comprehensive understanding of AI capabilities affect the risk management practices and resilience of enterprises. This study makes significant theoretical and empirical contributions. Theoretically, the study advances the literature on AI-based risk governance by establishing relationships between technological capabilities and risk-related outcomes and resilience. Empirically, the study contributes to the literature by providing insights into the relationships between AI capability and financial risk management and business resilience.

2. Materials and Methods

Research Design and Conceptual Framework

In this study, the quantitative cross-sectional approach was used in exploring the impact of the AI capability on enterprise financial risk management and resilience. The theoretical framework was formulated based on the three dimensions of AI capability: AI Risk Assessment Capability, AI Risk Prediction Capability, and AI Decision-Making Capability [15]. These dimensions were analyzed against the background of such dependent variables as Financial Risk Management Effectiveness, Risk Response Agility, and Business Resilience [16]. It is expected that the higher level of AI capability leads to the better performance of the firm in terms of the identification and prediction of the financial risks, making timely and high-quality decisions concerning the risks and the ability to react to the financial disruptions [17].

Study Population and Online Survey

The study considered the population of professionals involved in areas such as finance, banking, accounting, risk management, information technology, data analytics, and other business operations within the United States. The sampling technique employed was purposive sampling, whereby participants who had expertise in financial risk management and use of AI for business processes were selected. Data collection entailed administering an online questionnaire to suitable participants. The questionnaire was sent through professional networks, organizational links, and professional online forums. After conducting the process of screening the responses received for completeness and quality of the responses, a total of 175 responses were considered for the analysis.

Survey Instrument and Variable Measurement

A well-designed questionnaire was used for collecting demographic data and measuring the main constructs of the study framework. It had two parts. The first part comprised demographic and occupational data including the respondent's gender, age, education level, and occupational experience [18]. The second part contained measures of AI capability and organizational performance. AI capability was measured through AI Risk Assessment Capability, AI Risk Prediction Capability, and AI Decision-Making Capability [19]. The dimensions of performance included Financial Risk Management Effectiveness, Risk Response Agility, and Business Resilience. The measures of each construct were composed of several items that corresponded to the specific dimensions of each construct. The answers were provided on the five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) [20].

Data Analysis and Statistical Procedures

Data collected were systematically coded, screened and analyzed using the IBM SPSS Statistics Version 29.0 [21]. Frequency and percentage analysis was used to determine the demographic attributes as well as patterns of AI capability adoption by the organizations [22]. Measures of descriptive statistics including the measures of central tendencies such as the mean, standard deviation, variance, minimum value, maximum value, and skewness were determined [23]. Pearson correlation analysis was carried out to determine the nature and the strength of relationship between AI capabilities, effectiveness in financial risk management, risk response flexibility, and business resilience [24]. Statistical significant of the hypothesized relationships was determined using regression coefficients, standard errors, t-values, and level of significance. Model fit was established using R^2, Adjusted R^2 and F-statistics [25].

3. Results

Demographic Profile and Professional Characteristics of Respondents

The demographics and professional information of the respondents who were involved in this research is highlighted in Table 1. More men were involved in this research sample at 60.6% compared to women, which contributed 39.4% to the total sample size. Looking at the age distribution of the respondents, the highest number came from the 31-40 age group contributing 38.9%, then those in the age group 41-50, who constituted 25.7% and those within the age of 21-30 years who constituted 20.0%. Those respondents above 50 years constituted 15.4% of the sample size. Education level showed that the sample respondents were highly educated with 52.0% having a master's degree, 27.4% had a bachelor's degree while 20.6% had a doctorate degree. Professional experience showed that 38.3% had 5-10 years of experience, while 25.7% had 11-15 years.

Table 1. Demographic Profile and Professional Characteristics of Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	106	60.6
Gender	Female	69	39.4
Age Group	21–30 years	35	20.0
Age Group	31–40 years	68	38.9
Age Group	41–50 years	45	25.7

Characteristic	Category	Frequency (n)	Percentage (%)
Age Group	>50 years	27	15.4
Education	Bachelor's degree	48	27.4
Education	Master's degree	91	52.0
Education	Doctorate	36	20.6
Professional Experience	<5 years	32	18.3
Professional Experience	5–10 years	67	38.3
Professional Experience	11–15 years	45	25.7
Professional Experience	>15 years	31	17.7

Descriptive Statistics of Study Variables

The demographic and professional characteristics of 175 people participated in the research are shown in Table 1. Males accounted for 60.6% of the number of respondents while the rest were females – 39.4%. According to the age structure of the respondents, the biggest part of the sample was aged 31-40 years, which took 38.9%, then aged 41-50 years (25.7%) and 21-30 years (20.0%). The part of respondents, which was older than 50 years, was equal to 15.4%. In terms of education, the respondent group seems to be highly educated because 52.0% of them had a master's degree, 27.4% a bachelor's degree and 20.6% - a doctoral degree. With regards to professional experience, 5-10 years and 11-15 years are the most common periods (38.3% and 25.7%, correspondingly), while those with experience of less than 5 years and more than 15 years account for 18.3% and 17.7%, respectively.

Table 2. Descriptive Statistics of Study Variables

Study Variable	Mean	SD	Variance	Skewness
AI Risk Assessment Capability (ARAC)	3.96	0.74	0.548	-0.42
AI Risk Prediction Capability (ARPC)	3.88	0.78	0.608	-0.36
AI Decision-Making Capability (AIDC)	3.91	0.72	0.518	-0.39
Financial Risk Management Effectiveness (FRME)	3.94	0.75	0.563	-0.44
Risk Response Agility (RRA)	3.86	0.79	0.624	-0.31
Business Resilience (BR)	4.02	0.69	0.476	-0.48

AI Capabilities Adopted for Enterprise Financial Risk Management

The distribution of AI capabilities employed for enterprise financial risk management as displays in Figure 1. Predictive Risk Analytics had the largest share of 26.3%, which indicates an increasing trend of using AI technologies to forecast possible financial risks. Automated Risk Assessment occupied the share of 22.3% and indicates a significant adoption rate of AI techniques for assessment of financial risk conditions. Real-Time Risk Monitoring covered 20.0%, indicating the necessity of continuous monitoring in order to identify any emerging risks. AI-Based Fraud Detection had the share of 17.7%, illustrating the significance of utilizing AI technologies in order to improve financial controls and detect any suspicious activity. Intelligent Decision Support had the smallest share of 13.7%, indicating a relatively low rate of adoption of AI-assisted managerial decision making.

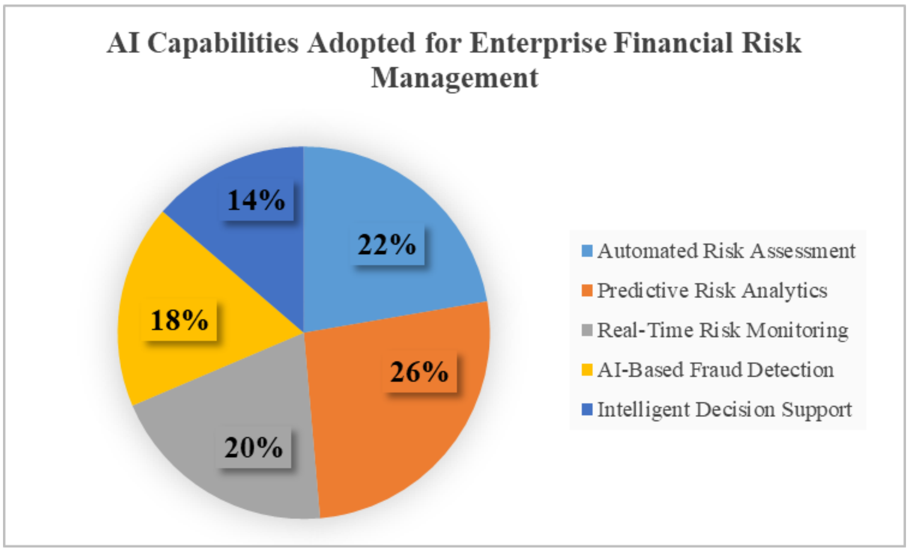

Figure 1. AI Capabilities Adopted for Enterprise Financial Risk Management

Perceived Benefits of AI-Enabled Financial Risk Management

The perceived benefits that arise from utilizing AI in financial risk management as shows in Figure 2. The most popular benefit was that of Improved Risk Identification with a 25.7% response rate, showing how well AI aids in early detection of risks in financial situations. Faster Risk Prediction was at 21.1%, illustrating the importance of predictive abilities in preparing for future risks. Improved Decision Making was 19.4%, revealing the role played by AI insights in decision making regarding finances. Reduced Financial Losses were 16.0%, showing how AI can be useful in reducing any financial losses resulting from the risk event. On the other hand, Faster Risk Response was 10.9%, depicting faster responses to risks. Enhanced Business Resilience showed a 6.9% response rate.

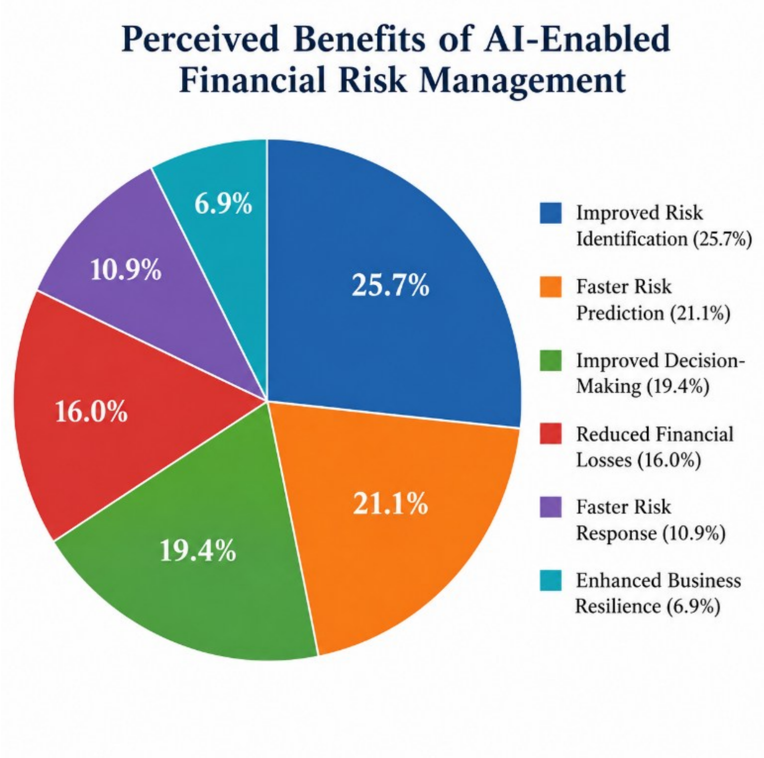

Figure 2. Perceived Benefits of AI-Enabled Financial Risk Management

Pearson Correlation Matrix among Study Variables

The Pearson correlation matrix can be seen in Figure 3 and indicates the consistent existence of positive correlations between the study variables. The most strongly correlated variables were the Financial Risk Management Effectiveness and Business Resilience with a correlation of 0.756, which means that the better the financial risk management is, the more resilient the organization will be. The variable Financial Risk Management Effectiveness had a positive correlation of 0.721 with Risk Response Agility and a positive correlation of 0.731 with AI Risk Prediction Capability. The variable AI Decision-Making Capability was positively correlated with Financial Risk Management Effectiveness at 0.716 and with Business Resilience at 0.713. As for the AI capabilities dimensions, the most strongly correlated variables were the AI Risk Prediction Capability and AI Decision-Making Capability with 0.704.

Table. Pearson Correlation Matrix among Study Variables

Variables	ARAC	ARPC	AIDC	FRME	RRA	BR
ARAC AI Risk Assessment Capability	1.000					
ARPC AI Risk Prediction Capability	0.672	1.000				
AIDC AI Decision-Making Capability	0.641	0.704	1.000			
FRME Financial Risk Management Effectiveness	0.698	0.731	0.716	1.000		
RRA Risk Response Agility	0.584	0.667	0.689	0.721	1.000	
BR Business Resilience	0.621	0.694	0.713	0.756	0.738	1.000

Note: ARAC = AI Risk Assessment Capability, ARPC = AI Risk Prediction Capability, AIDC = AI Decision-Making Capability, FRME = Financial Risk Management Effectiveness, RRA = Risk Response Agility, BR = Business Resilience.

Figure 3. Pearson Correlation Matrix among Study Variables

Hypothesis Testing and Structural Relationship Analysis

Structural relations and findings of hypothesis testing as contains Table 3. All six suggested hypotheses have proven their validity as all of them were statistically significant at $p < 0.001$. Among the AI capability measures, AI Risk Prediction Capability has exhibited the highest level of influence on Financial Risk Management Effectiveness ($\beta = 0.314$), followed by AI Risk Assessment Capability ($\beta = 0.286$) and AI Decision-Making Capability ($\beta = 0.267$). The highest correlation between Financial Risk Management Effectiveness and Risk Response Agility ($\beta = 0.582$) suggests that more efficient financial risk management significantly increases the organization's ability to respond to the emerging risks. The relationship between Risk Response Agility and Business Resilience ($\beta = 0.438$) has also been significant. Financial Risk Management Effectiveness has had a significant direct impact on Business Resilience ($\beta = 0.351$). The model was able to explain 67.2% of the Business Resilience variance with an adjusted $R^2 = 0.660$ and overall F-statistic of 72.84.

Table 3. Hypothesis Testing and Structural Relationship Analysis

Hypothesis	Structural Relationship	β	SE	t-value	p-value	Decision
H1	ARAC → FRME	0.286	0.061	4.69	<0.001	Supported
H2	ARPC → FRME	0.314	0.064	4.91	<0.001	Supported
H3	AIDC → FRME	0.267	0.059	4.53	<0.001	Supported
H4	FRME → RRA	0.582	0.067	8.69	<0.001	Supported
H5	RRA → BR	0.438	0.063	6.95	<0.001	Supported
H6	FRME → BR	0.351	0.065	5.40	<0.001	Supported

Model Summary	
Statistic	**Value**
R^2 (Business Resilience)	0.672
Adjusted R^2	0.660
F-statistic	72.84

4. Discussion

These results offer some crucial insights about the significance of artificial intelligence capability in the area of enterprise financial risk management and business resilience. Based on the respondents' profile, one may argue that the research has managed to include views of an adequately experienced and academically educated group of people, which can be considered a proper background for evaluating financial activities based on AI technology [26]. As for the results of the descriptive analysis, all constructs show overall positive results. The Business Resilience construct demonstrated the highest average value of 4.02, followed by the AI Risk Assessment Capability (3.96) and the Financial Risk Management Effectiveness (3.94). This finding implies that firms realize the necessity of AI in the process of risk identification and organizational sustainability [27]. The relatively high estimates of AI Decision-Making Capability and AI Risk Prediction Capability indicate that the use of AI in risk management goes beyond the scope of specific operations [28].

The adoption pattern gives yet another perspective on the role played by AI in financial risk management today. Predictive Risk Analytics came first with 26.3% adoption, followed by Automated Risk Assessment with 22.3% and Real-Time Risk Monitoring with 20.0%. Clearly, much importance is given to technologies which will be able to detect patterns, predict threats and monitor financial state. Relatively smaller figure when it comes to Intelligent Decision Support with 13.7% shows that the use of AI for the purpose of making business decisions is still being developed. It becomes clear after looking at the benefits perceived by companies as well. Improved Risk Identification takes the lead with 25.7% followed by Faster Risk Prediction with 21.1% and Improved Decision-Making with 19.4%. These results suggest that the value that an organization receives from AI usage is highly evident when it comes to improving risk identification and prediction [29].

The correlation analysis shows positive relationships among the variables used in the study. The strongest relationship was found between Financial Risk Management Effectiveness and Business Resilience, at $r = 0.756$, thus revealing a close relationship between the effectiveness of financial risk management and an ability of organizations to survive during financial crises. Financial Risk Management Effectiveness also showed strong relationships with AI Risk Prediction Capability, at $r = 0.731$, and Risk Response Agility, at $r = 0.721$. These results indicate that the predictive capability of AI can help to build efficient processes of financial risk management and respond to the emerging risks. Finally, the relationship between AI Decision-Making Capability and Business Resilience, at $r = 0.713$, reveals that the role of AI goes far beyond risk prediction and is also related to the decision-making process within organizations.

Results from hypothesis testing also provided further empirical support to the suggested relationships. All the six hypotheses were confirmed at $p < 0.001$. Thus, there were significant positive structural relationships between the study variables. Of the three AI capability dimensions, AI Risk Prediction Capability proved to have the highest effect on Financial Risk Management Effectiveness with $\beta = 0.314$, AI Risk Assessment Capability – with $\beta = 0.286$ and AI Decision-Making Capability – with $\beta = 0.267$. It underlines the specific value of predictive intelligence in today's financial risk management [30]. The most significant structural relationship in the model was found to exist between Financial Risk Management Effectiveness and Risk Response Agility with $\beta = 0.582$. It means that the effectiveness of financial risk management is associated with an organization's capacity to react quickly and adequately to financial risks [31]. In addition, Risk Response Agility positively affected Business Resilience with $\beta = 0.438$, and Financial Risk Management Effectiveness positively affected Business Resilience with $\beta = 0.351$ directly. These relations demonstrate that, besides having the technological ability, resilience also depends on how well the generated AI-based intelligence is integrated into organizational risk management [2]. The model accounted for 67.2% of the variation in Business Resilience and has Adjusted R^2 equal to 0.660, which proves high predictive power. Combining AI-based risk assessment, prediction analytics and decision making with good financial risk management may enhance the risk response process and lead to higher resilience of the company's operations. For companies which operate in increasingly complex financial conditions, combining such interrelated capabilities may prove useful.

5. Conclusion

This study illustrates that the ability to leverage AI is an essential factor that increases the effectiveness of financial risk management in business and makes business more resilient. AI Risk Prediction Ability had the highest impact on all the other factors. On the other hand, Financial Risk Management Effectiveness significantly increased the Risk Response Agility. Positive correlations between all the factors in the study additionally indicate the interdependent nature of these factors. The model accounted for 67.2% of the variation in Business Resilience, illustrating the high explanatory ability of the model.

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