Power System Protection and Control
ISSN:1674-3415

THE IMPACT OF PREDICTIVE INTELLIGENCE AND REAL-TIME DATA INSIGHTS ON CORPORATE FINANCIAL SUSTAINABILITY

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Received: 14/05/2026 **Revised**: 18/06/2026 **Accepted**: 25/07/2026

***ABSTRACT*:**

Purpose: This study examines the impact of Predictive Intelligence (PI) and Real-Time Data Insights (RDI) on Corporate Financial Sustainability (CFS), while controlling for organizational factors, industry factors, and AI-related risk factors. The research aims to determine whether these analytic capabilities (PI and RDI) individually and jointly contribute to long-term financial resilience and performance in modern organizations.

Theoretical Framework: The study is grounded in three complementary theoretical perspectives: the Resource-Based View, which conceptualizes PI and RDI as strategic organizational capabilities; Dynamic Capability Theory, which explains how sensing (PI) and seizing/reconfiguration (RDI) functions enable firms to adapt to changing environments; and the Data-Driven Decision-Making perspective, which emphasizes the role of timely, analytically processed data in improving decision quality and financial outcomes.

Methodology: A quantitative, cross-sectional research design was adopted, with data collected from 320 managerial and analytical professionals across medium and large organizations in multiple countries and industries, including Financial Services, Manufacturing, Information Technology, and Retail/Trade. Reliability and validity tests, including Cronbach's alpha, Exploratory Factor Analysis (EFA), and Harman's Single Factor Test for common method bias, were conducted, and measurement methods were adapted from validated scales.

Key Findings: The results provided strong support for all three hypotheses. PI had a significant positive effect on CFS ($\beta = 0.410$, $p < 0.001$, $\Delta R^2 = 0.144$), and RDI similarly demonstrated a significant positive influence ($\beta = 0.370$, $p < 0.001$, $\Delta R^2 = 0.133$). When entered together, PI and RDI jointly explained an additional 19.7% of variance in CFS ($\Delta R^2 = 0.197$, $p < 0.001$), confirming their complementary and synergistic contributions. Among controls, OF consistently showed a strong positive effect, IF was positive but marginally significant, and AR exhibited a significant negative relationship with CFS across all models.

Originality/Value: This study contributes to the literature by empirically distinguishing PI and RDI as separate but complementary analytics capabilities, demonstrating that their combined use provides a more comprehensive explanation of financial sustainability than either construct alone. It also highlights the importance of managing AI-related risks to realize the full potential of analytics investments. The findings offer practical guidance for organizations seeking to leverage AI-enabled predictive and real-time analytics for long-term financial resilience.

Keywords: *Predictive Intelligence, Real-Time Data Insights, Corporate Financial Sustainability, Business Analytic, Financial Risk Management.*

INTRODUCTION

Financial organizations increasingly prioritize sustainability, incorporating social-environmental welfare, economic growth, and governance together to the traditional profit-focused performance appraisal. More investment is drawn in by improved financial transparency brought about by advanced accounting and technology. Including sustainability data in financial statements improves long-term growth, investor trust, and performance forecasting. These goals are further reinforced by the 17 SDGs set forward by the UN (Mahlha et al., 2025). In the end, organizational trust and responsibility are strengthened by sustainable transparency. Financial business ESG reporting has improved due to the availability of big data, which is validated by important accounting organizations like FASB and AICPA. Enhancing financial institutions currently heavily relies on integrating ESG

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ISSN:1674-3415

problems with investing strategies (Rahman, 2024). Data analytics gathers important information for the growth of the financial market. By accurately analyzing future trends, consumer behavior, and risks, predictive analytics enhances operational efficiency (Oyeniyi et al., 2024). Additionally, it facilitates compliance monitoring and fraud detection (Nwoke, 2025).

The stability, competitiveness, and long-term viability of a financial organization lay the foundation for corporate financial sustainability, which helps manage a dynamic and uncertain business environment. Operational continuity and long-term capacity to meet stakeholder expectations were ensured through the establishment of corporate finance sustainability. Hossain et al. (2022) state that the present capital consumption was efficiently balanced, which is considered a major strength of the financial organization and helps satisfy the needs of future stakeholders. Kong et al. (2023) highlighted that long-term success and financial stability were assured by effective management of organizational funds. Responsible financial management, supported by enduring growth, ensures sustainability in a financial organization. Moreover, the long-term sustainability of an organization depends on measuring and assessing financial risk. The resilience, profitability, and financial strength of an organization were measured using financial indicators.

Traditional financial monitoring approaches often rely on historical data, which limits organizations' ability to anticipate risks and make proactive strategic decisions. Recent advances in predictive intelligence, leveraging AI and machine learning techniques, provide forward-looking analyses that improve financial forecasting, detect emerging risks, and support timely managerial interventions (Das & Swain, 2025). Empirical studies have demonstrated that AI-powered predictive analytics significantly improve forecasting accuracy, risk mitigation, and strategic decision-making in corporate financial contexts (Celestin & Mishra, 2025). In addition, AI integration supports corporate sustainability objectives by enabling long-term financial resilience and proactive resource allocation (Elhady & Shohieb, 2025). urrently, there is limited empirical evidence examining the joint influence of predictive intelligence and real-time data insights on corporate financial sustainability, while accounting for these organizational, industry, and AI-related risk factors. Addressing this gap is crucial to providing evidence-based guidance for organizations aiming to implement AI-enabled predictive systems effectively.

1.1 Research Problem

Proactive risk anticipation and strategic decision-making are limited by traditional financial monitoring's dependency on historical data. By utilizing AI and ML, advancements in predictive intelligence (PI) allow for forward-looking studies that enhance forecasting, identify new dangers, and facilitate prompt actions (Das & Swain, 2025). However, confounding organizational factors (e.g., management quality, firm size), industry factors (e.g., trends, volatility), and AI-related risks (e.g., overreliance, alert fatigue, data quality issues) make it difficult to isolate the direct effects of PI and Real-Time Data Insights (RDI) on Corporate Financial Sustainability (CFS) (Ao, 2025). Further limiting efficacy are possible drawbacks including an excessive dependence on AI forecasts, alert fatigue, or misunderstanding of real-time information (Rakibul et al., 2024).

Currently, there is limited empirical evidence examining the joint influence of predictive intelligence and real-time data insights on corporate financial sustainability, while accounting for these organizational, industry, and AI-related risk factors. Therefore, this study aims to examine the effects of predictive intelligence (PI), assess the role of real-time data insights (RDI), and evaluate their combined impact on corporate financial sustainability (CFS), while controlling for organizational, industry, and AI-related risk factors. This will contribute to both the theoretical understanding and practical implementation of AI-driven financial risk management. We framed three major research questions, which will be investigated in this research.

1. What is the impact of predictive intelligence on corporate financial sustainability?
2. How do real-time data insights influence financial sustainability?
3. How do predictive intelligence and real-time data insights jointly affect corporate financial sustainability outcomes?

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Resource-Based View Theory

The Resource-Based View (RBV) explains firm performance in terms of the strategic resources and capabilities that organizations possess and deploy. According to RBV, firms achieve sustainable advantage when they develop

DOI: 10.46121/pspc.54.3.33

Power System Protection and Control
ISSN:1674-3415

valuable, rare, difficult-to-imitate, and organizationally embedded resources. Big data analytics and organizational capabilities are seen as strategic assets that assist companies in transforming data into improved performance and decision-making (Akter et al., 2016; Wamba et al., 2017). Subsequent research supports the RBV perspective by confirming that they enhance market, operational, and sustained competitiveness (Aziz et al., 2023b; Malik, 2024). In the context of the present study, PI and RDI insights can be understood as strategic organizational capabilities rather than merely technical tools. Predictive intelligence enables firms to anticipate financial risks, forecast outcomes, and improve planning quality, while real-time data insights allow organizations to monitor changing conditions and respond quickly to emerging issues. From an RBV perspective, the study therefore assumes that firms with stronger predictive and real-time analytics capabilities are better positioned to sustain financial resilience and performance over time (Chatterjee et al., 2023).

2.2. Dynamic Capability Theory

Dynamic Capability Theory extends the RBV by emphasizing not only the possession of resources but also the firm's ability to integrate, reconfigure, and deploy those resources in response to changing environments. This perspective is especially relevant in volatile and data-intensive business settings, where organizations must continually sense opportunities and threats, seize them through decision-making, and transform internal processes accordingly. More recent studies have similarly argued that analytics-enabled dynamic capabilities improve agility, innovation, and organizational performance under changing market conditions (Yoshikuni et al., 2025; Wong & Ngai, 2025). This concept is extremely pertinent because Real-Time Data Insights (RDI) promotes seizing and reconfiguring by enabling quick reactions to changing situations, while Predictive Intelligence (PI) improves organizational sensing by identifying future patterns and hazards. Although implemented together, these abilities enhance sustainable financial performance, decrease strategic delays, and increase financial responsiveness. Dynamic Capability Theory therefore provides a strong explanation for why PI and RDI are expected to enhance corporate financial sustainability in contemporary organizations (Chatterjee et al., 2023).

2.3. Data-Driven Decision-Making (DDDM) Perspective

In financial management, where decision speed and quality influence forecasting, risk control, and long-term outcomes, the data-driven decision-making perspective maintains that organizations could enhance decision quality by relying on timely, analytically processed data rather than intuition. According to recent research, big data analytics improves forecasting, decision-making, and firm performance all at once (Fattah, 2024; Lee & Kim, 2023). Within this perspective, PI supports forward-looking decision-making by translating historical and current data into forecasts and scenarios, while real-time data insights support immediate decision-making by providing up-to-date visibility into financial conditions. Together, these capabilities can improve the quality, speed, and confidence of financial decisions. This is especially relevant for corporate financial sustainability, which depends on timely risk responses, informed planning, and effective allocation of financial resources. Accordingly, the data-driven decision-making perspective complements RBV and Dynamic Capability Theory by explaining the direct decision-quality mechanisms through which PI and RDI may influence CFS (Khan & Saha, 2024).

2.4. Analytical Framework and Hypotheses Development

2.4.1. Analytical Framework

The conceptual framework of the present study is developed from the literature on analytics capability, financial decision-making, and organizational performance. The framework proposes that Predictive Intelligence (PI) and Real-Time Data Insights (RDI) are the main explanatory variables influencing Corporate Financial Sustainability (CFS), as illustrated in Figure 1.

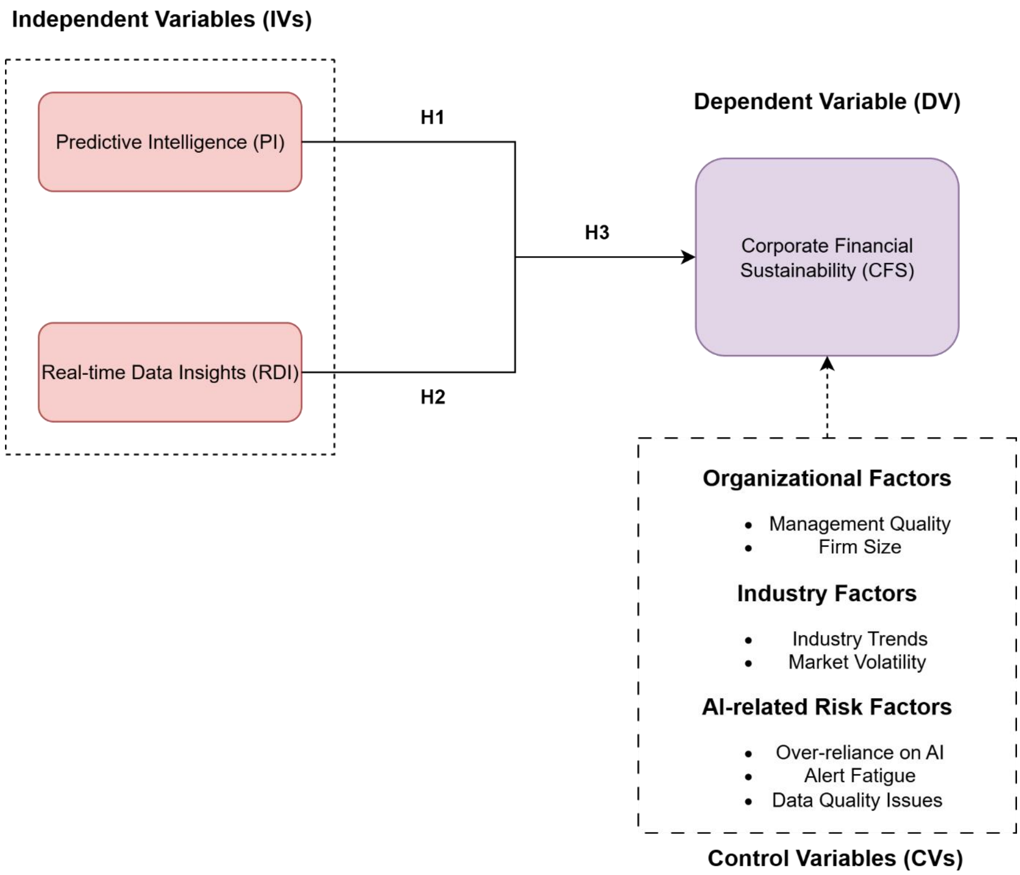

Figure 1: Analytical Framework.

Predictive Intelligence refers to the organization's ability to use advanced analytics, artificial intelligence, and predictive models to forecast future outcomes, anticipate risks, and support strategic financial planning (Unalp, 2024). Real-Time Data Insights refer to the organization's ability to access, process, and interpret current data quickly enough to support immediate managerial responses and continuous monitoring of financial conditions (Olayinka, 2021; Alonge et al., 2023). Corporate Financial Sustainability refers to the ability of the organization to maintain long-term financial resilience, stable financial performance, effective risk control, and sustainable resource allocation.

In conformity to the framework, RDI Insights enable continuous monitoring and quick response to market changes, supporting financial stability, while PI is anticipated to enhance CFS through improved forecasting, risk prediction, and strategic planning. These connections are consistent with other research showing that analytical skills enhance predicting, decision-making, and business success (Wamba et al., 2017; Chatterjee et al., 2023). To separate the distinct contributions of PI and RDI to CFS, the approach additionally incorporates control factors, such as management quality, company size, industry trends, market volatility, and AI-related hazards (such as overreliance, alert fatigue, and data quality). In accordance to the model, organizations can manage fluctuation and sustain financial performance by integrating Predictive Intelligence (future-oriented, concentrating on forecasting and long-term planning) and Real-Time Data Insights (present-oriented, enabling immediate monitoring and rapid response) (Al-Okaily & Al-Okaily, 2025b). They capture complementary but non-overlapping analytical capabilities according to their unique temporal orientations.

2.5. Hypotheses Development

2.5.1. Predictive Intelligence (PI) and Corporate Financial Sustainability (CFS)

PI has become increasingly important in corporate finance because it enables firms to move from retrospective reporting to forward-looking financial management. By combining AI, ML, and predictive analytics, organizations can improve financial forecasting, detect risks, and develop more informed strategic plans. Prior research has shown that analytics capability improves forecasting, decision-making, and firm performance, while

DOI: 10.46121/pspc.54.3.33

predictive modeling in financial contexts enhances risk management and resource allocation (Chatterjee et al., 2023). Studies on analytics capability and firm performance have also suggested that firms with stronger analytics capabilities are better able to improve internal processes and long-term performance outcomes (Aydiner et al., 2019). From the perspective of this study, organizations that use predictive intelligence effectively are expected to achieve stronger corporate financial sustainability because they can anticipate cash flow pressures, detect potential financial threats, and allocate resources more proactively. As a result, predictive intelligence should contribute positively to long-term financial resilience and stability.

H1: Predictive intelligence has a significant positive effect on corporate financial sustainability.

2.5.2. Real-Time Data Insights and Corporate Financial Sustainability

Real-time data insights are increasingly important in organizational decision-making because they allow managers to access current information and respond immediately to changing environment. In financial environments, the value of real-time data lies in its ability to support continuous monitoring of transactions, financial risks, operational deviations, and market changes. Recent research has shown that analytics capability improves decision-making performance and organizational responsiveness, and studies on real-time and streaming analytics have emphasized its role in enabling immediate, actionable decisions across business functions (Khan & Saha, 2024). In financial settings, real-time analytics supports faster forecasting updates, improved risk visibility, better fraud detection, and more agile financial control (Odogwu et al., 2023; Fattah, 2024). Firms that can access and interpret real-time financial information are more likely to maintain cash flow stability, reduce response delays, and manage emerging financial risks.

H2: Real-time data insights have a significant positive effect on corporate financial sustainability.

2.5.3. Joint Effect of Predictive Intelligence and Real-Time Data Insights on Corporate Financial Sustainability

Although PI and RDI insights each provide value independently, the literature suggests that their combined use may produce stronger outcomes. Together, these capabilities create a more complete decision architecture in which firms can anticipate future risks while simultaneously responding to current developments. Research on analytics capability indicates that firms gain greater performance benefits when analytics is integrated into broader decision and process systems rather than used in isolation (Aljehani et al., 2024). Studies have also found that analytics capability, agility, and dynamic capabilities jointly contribute to stronger firm performance and adaptability (Bonsu & Guo, 2026). In the present study, the joint effect of PI and RDI is expected to be especially important for corporate financial sustainability. From a theoretical perspective, the joint effect of predictive intelligence and real-time data insights is supported by the integration logic of Dynamic Capability Theory and the data-driven decision-making perspective. While predictive intelligence enhances the sensing of future opportunities and risks, real-time data insights strengthen the seizing and reconfiguration processes by enabling immediate response. Their combined use therefore enhances both anticipatory and adaptive decision-making, leading to stronger financial sustainability outcomes.

H3: Predictive intelligence and real-time data insights jointly explain significant variance in corporate financial sustainability.

METHODOLOGY

This chapter outlines the methodology used to examine both the individual and joint additive effects of predictive intelligence and real-time data insights on corporate financial sustainability. This study used deductive research approach that examines the impact of Real-Time Data Insights (RDI) and Performance Indicators (PI) on Corporate Financial Sustainability (CFS) employing a positivist approach that incorporates quantitative and objective data.

3.1. Methodological Choice: Quantitative Research Design

This study adopts a quantitative research design, as it aims to examine measurable relationships among PI, RDI, and CFS through hypothesis testing.The present research focuses on testing the direct and joint additive effects of PI and RDI on CFS using measurable constructs. Therefore, a quantitative approach is most appropriate, as it provides the analytical rigor required to examine relationships among variables using statistical techniques such as correlation analysis and hierarchical multiple regression. This approach also allows for the inclusion of control variables, including organizational, industry, and AI-related risk factors, without altering the core relationships being tested.

DOI: 10.46121/pspc.54.3.33

This is a cross-sectional study and data was collected using a structured questionnaire at a particular point of time. This corresponds for analyzing associations between PI, RDI and CFS, rather than temporal dynamics. It enables statistical testing of relationships, while controlling for organizational, industry and AI-related risk factors. Even though causal inferences are limited and should be interpreted with caution, the design is well suited to identify significant associations within the scope of the study.

3.2. Target Population, Unit of Analysis and Data Collection Method

In this study, the target population comprises medium and large organizations that have adopted advanced analytics and AI-based systems in their financial management processes, across multiple countries and industry sectors in order to enhance contextual diversity and external validity. Organizations from countries such as India, the United States, the United Kingdom, Germany, Singapore, the United Arab Emirates, Saudi Arabia, and Japan are represented in the study. Within these organizations, data are collected from managerial and analytical professionals who are directly involved in financial and analytics-related functions. The unit of analysis can be either an individual, a group, an organization, or an entire industry, depending on the research goals (Hossan et al., 2023). The unit of analysis in this study is the organization, although data are collected from individual respondents, their responses reflect organizational practices rather than personal opinions.

A survey method using a structured questionnaire is adopted (Ghanad, 2023). In this study, the survey instrument is designed to measure organizational capabilities related to predictive intelligence, real-time data insights, and corporate financial sustainability. The use of a structured survey ensures that responses are collected in a consistent and standardized manner, allowing for reliable coding and statistical analysis (Alordiah & Ossai, 2023). Data has been collected by online questionnaire, To enhance the response rate, the questionnaire link was distributed through professional networks, corporate contacts, and industry-related groups.

3.3. Questionnaire Design and Instrumentation

Brief and simplified definitions of technical terms were provided at the beginning of each section in Questionnaire. It helps to reduce measurement error and improves the reliability and validity of responses by ensuring that all participants share a common understanding of the constructs being measured. The questionnaire is organized into five main sections:

1. Section A: Respondent and Organizational Profile
   This section collects general information about the respondents and their organizations, including age, gender, job position, industry classification, and organizational characteristics. The questionnaire also includes organizational contextual information such as country of organization and an optional organization name field to support contextual interpretation and geographical analysis while maintaining respondent confidentiality.
2. Section B: Predictive Intelligence (PI)
   This section measures predictive intelligence as a future-oriented organizational capability. PI refers to the use of advanced analytics, artificial intelligence, and machine learning techniques to forecast financial outcomes, anticipate risks, and support strategic planning.

The measurement items assess the extent to which organizations:

- use predictive models for financial forecasting
- apply analytics to identify potential risks
- utilize scenario analysis for strategic decision-making

These items capture the organization's ability to anticipate future financial conditions and improve long-term planning.

3. Section C: Real-Time Data Insights (RDI)
   This section measures real-time data insights as a present-oriented organizational capability. RDI refers to the ability of organizations to access, process, and utilize up-to-date data to support immediate decision-making and operational responsiveness.

The measurement items assess:

- the speed of data availability
- integration of real-time data sources
- the extent to which real-time information supports rapid managerial decisions

DOI: 10.46121/pspc.54.3.33

Power System Protection and Control
ISSN:1674-3415

These items capture the organization's capability to monitor financial conditions continuously and respond promptly to emerging risks and opportunities.

4. Section D: Corporate Financial Sustainability (CFS)

This section measures the dependent variable, corporate financial sustainability. CFS reflects the organization's ability to maintain stable financial performance and long-term resilience.

The measurement items capture:

- sustainable profitability
- cash flow stability
- effective financial risk management
- long-term resource allocation

These indicators represent the organization's capacity to sustain financial performance over time.

5. Section E: Control Variables

This section includes control variables used to isolate the effects of the main independent variables. These include:

- organizational factors (e.g., firm size, management quality)
- industry factors (e.g., market volatility, industry trends)
- AI-related risk factors (e.g., overreliance on AI, data quality issues, alert fatigue)

3.3.1.Measurement Scale and Instrument Validation

All perceptual items in the questionnaire are measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Likert scales are widely used in management and information systems research due to their effectiveness in capturing attitudes, perceptions, and organizational practices, while also enabling robust statistical analysis (Koo & Yang, 2025). To reduce potential response bias, selected items are reverse-coded, and a marker variable is included to assess common method bias.

3.4. Measurement of Variables

The measurement items used in this study are adapted from established literature to ensure consistency with prior research. Most constructs are measured using perceptual indicators on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This approach allows respondents to evaluate the extent to which their organizations adopt PI and RDI and how these capabilities influence corporate financial sustainability.

The operationalization of variables is summarized in Table 1, which presents the variable type, measurement indicators, scale, and sources of measurement items.

Table 1: Measurement of Variables

Variable Type	**Variable**	**Measurement Indicators**	**Scale / Source**
Independent Variables (IVs)	Predictive Intelligence (PI)	Accuracy of financial forecasts; Effectiveness in risk prediction; Scenario planning capability	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree); adapted from Celestin & Mishra (2025), Das & Swain (2025)
	Real-Time Data Insights (RDI)	Speed of data collection; Integration of internal and external financial data; Support for rapid managerial decision-making	5-point Likert scale; adapted from Najem et al. (2025), Elhady & Shohieb (2025)
Dependent Variable (DV)	Corporate Financial Sustainability (CFS)	Sustainable profitability; Cash-flow consistency; Financial risk mitigation; Long-term resource allocation	5-point Likert scale; adapted from Das (2024), Celestin & Mishra (2025)
Control Variables (CVs)	Organizational Factors	Management Quality: leadership effectiveness, strategic planning capability, decision-making efficiency; Firm Size: number of employees or annual revenue	Management Quality measured using a 5-point Likert scale adapted from Ao (2025); Firm Size measured using objective indicators.
	Industry Factors	Industry Trends: perceived sector growth and competitiveness; Market Volatility:	5-point Likert scale; adapted from Ao (2025) and industry reports

DOI: 10.46121/pspc.54.3.33

Power System Protection and Control
ISSN:1674-3415

		perceived frequency and magnitude of market fluctuations	
	AI-related Risk Factors	Overreliance on AI; Alert fatigue; Data quality issues (accuracy, completeness, reliability)	5-point Likert scale; adapted from Das & Swain (2025), Najem et al. (2025), Rakibul et al. (2024)

3.5. Data Analysis Procedure

IBM SPSS Statistics was used to analyze the data collected through the structured questionnaire. The statistical analysis aimed to examine the relationships between predictive intelligence (PI), real-time data insights (RDI), and corporate financial sustainability (CFS), while controlling for organizational factors, industry conditions, and AI-related risk factors. The analysis was conducted in a systematic sequence, including descriptive statistics, correlation analysis, hierarchical multiple regression analysis, and regression assumption testing.

3.5.1. Data Screening and Preparation

Prior to conducting the statistical analyses, the collected responses were screened and prepared, the screening procedures included response verification, missing data assessment, outlier examination, reverse coding, and preparation of composite variables. Incomplete questionnaires, duplicate responses, inconsistent response patterns, and cases that did not satisfy the study inclusion criteria were excluded from the dataset. Outlier assessment was conducted using standardized z-score values, where values within the threshold range of ±3 indicated the absence of severe uni variate outliers. In addition, negatively worded items were reverse coded to ensure consistency in scale interpretation. Subsequently, composite mean scores were computed for all study constructs and used in the subsequent statistical analyses.

3.5.2. Descriptive Statistics and Normality Analysis

Descriptive statistics were used to summarize the characteristics of the dataset and provide an overview which included minimum values, maximum values, mean scores, and standard deviations for all study variables. These statistics assisted in understanding the overall level of agreement or disagreement with questionnaire items related to PI, RDI, CFS, and the control variables. In addition, demographic analysis was conducted to summarize respondent and organizational characteristics, including gender, age, job position, years of professional experience, AI/analytics usage, AI/analytics usage duration, and industry sector. Normality analysis was further conducted using skewness and kurtosis statistics together with histogram analysis. Skewness and kurtosis values within the acceptable threshold range of ±2 were considered indicative of acceptable normality for subsequent parametric statistical analyses (Alabi & Bukola, 2023).

3.5.3. Common Method Bias Diagnostics

The study relied on cross-sectional, self-reported data collected from single respondents, the possibility of common method bias (CMB) was considered. To assess this issue, Harman's Single-Factor Test was conducted by entering all measurement items into an unrotated exploratory factor analysis. If a single factor does not account for more than 50 percent of the total variance, common method bias is considered unlikely to represent a serious concern. In addition, construct distinctiveness was indirectly examined during Exploratory Factor Analysis by assessing whether measurement items loaded appropriately on their intended constructs.

3.5.4. Correlation Analysis

Pearson's correlation coefficient was used to assess the linear relationships between Predictive Intelligence (PI), Real-Time Data Insights (RDI), Corporate Financial Sustainability (CFS), and the control variables. This analysis provided preliminary evidence regarding the associations among variables prior to conducting hierarchical multiple regression analysis. Furthermore, correlation analysis assisted in identifying potential multicollinearity concerns among predictor variables. Correlation coefficients below the commonly accepted threshold value of 0.80 indicated the absence of severe multicollinearity among the independent variables, supporting their suitability for regression analysis (Selvamuthu & Das, 2024).

3.5.5. Hierarchical Multiple Regression Analysis

This technique allows the researcher to examine the influence of multiple independent variables on a single dependent variable while introducing predictors in a block-wise manner to test the research hypotheses. In this

DOI: 10.46121/pspc.54.3.33

study, Corporate Financial Sustainability (CFS) served as the dependent variable, while Predictive Intelligence (PI) and Real-Time Data Insights (RDI) were treated as the primary independent variables.

The hierarchical regression analysis was conducted in four models:

- Model 1 (Control Variables Model): Organizational Factors (OF), Industry Factors (IF), and AI-Related Risk Factors (AR) were entered as control variables to account for contextual organizational and environmental influences on Corporate Financial Sustainability.
- Model 2 (Predictive Intelligence Model): Predictive Intelligence (PI) was added together with the control variables to examine its additional explanatory contribution to Corporate Financial Sustainability.
- Model 3 (Real-Time Data Insights Model): Real-Time Data Insights (RDI) was added together with the control variables to examine its additional explanatory contribution to Corporate Financial Sustainability.
- Model 4 (Combined Explanatory Model): Predictive Intelligence (PI) and Real-Time Data Insights (RDI) were simultaneously entered together with the control variables to evaluate their combined explanatory contribution to Corporate Financial Sustainability.

The coefficient of determination (R^2) and the change in explained variance (ΔR^2) were used to evaluate the explanatory contribution of each regression model. Standardized beta coefficients (β values), t-values, F-statistics, and significance levels were used to assess the direction and significance of relationships between predictor variables and Corporate Financial Sustainability (Selvamuthu & Das, 2024).

3.5.6. Regression Assumption Testing

To ensure the validity and reliability of the hierarchical regression results, several diagnostic tests were conducted to verify the assumptions of multiple regression analysis.

- Multicollinearity: Multicollinearity among the predictor variables was assessed using Variance Inflation Factor (VIF) values. VIF values below the threshold value of 5 indicated the absence of severe multicollinearity.
- Independence of Errors: The independence of residuals was evaluated using the Durbin–Watson statistic. Values close to 2 indicated the absence of autocorrelation problems in the regression residuals.
- Homoscedasticity and Linearity: Homoscedasticity and linearity were examined using scatterplots of standardized residuals against standardized predicted values. A random and evenly distributed residual pattern without obvious funnel-shaped or curved structures indicated that the assumptions of homoscedasticity and linearity were satisfied.
- Normality of Residuals: The normality of residuals was assessed using histogram analysis and normal probability (P-P) plots of regression standardized residuals. Residual distributions approximating normality indicated that the regression models were statistically appropriate.

Confirming these assumptions was essential to ensure that the regression estimates were reliable and that the identified relationships accurately reflected the underlying data structure.

3.5.7. Hypothesis Testing

The research hypotheses were tested based on the results of the hierarchical regression analysis:

- H1: The effect of predictive intelligence (PI) on CFS was evaluated using the significance and direction of the β coefficient in the final regression model.
- H2: The effect of real-time data insights (RDI) on CFS was assessed using the β coefficient and significance level in the final model.
- H3: The combined contribution of PI and RDI was evaluated using the change in R^2 (ΔR^2) and the overall significance of the final regression model, indicating the joint explanatory power of both variables.

3.5.8. Reliability Analysis

The analysis was conducted using IBM SPSS Statistics, where the responses to each set of measurement items were entered to compute Cronbach's alpha values. Constructs with reliability coefficients above the acceptable threshold were considered reliable for further statistical analysis. Ensuring internal consistency confirms that the measurement items within each construct are stable and consistent across respondents, thereby enhancing the credibility of the research findings (Adeyemi, 2024).

3.5.9. *Content Validity*

Content validity refers to the extent to which the measurement items adequately represent all dimensions of the construct being measured. It ensures that the questionnaire captures the full conceptual domain of the variables included in the study (Adeyemi, 2024). In this research, content validity was established by adapting measurement items from previously validated studies related to predictive intelligence (PI), real-time data insights (RDI), and corporate financial sustainability (CFS). The use of established scales enhances the conceptual accuracy and consistency of the measurement instrument. Furthermore, the questionnaire items were carefully reviewed to ensure clarity of wording, relevance to research objectives, and alignment with the conceptual framework. This process ensured that the measurement items accurately reflect the constructs under investigation and are easily understood by respondents.

3.5.10. *Construct Validity*

Construct validity was assessed using Exploratory Factor Analysis (EFA) in SPSS, following suitability checks via KMO (> 0.60) and Bartlett's test ($p < 0.05$). Principal Component Analysis with Varimax rotation was applied, retaining factors with eigenvalues > 1 and item loadings ≥ 0.50. Items with low loadings or cross-loadings were considered for removal. Special attention was given to ensuring that Predictive Intelligence (PI) and Real-Time Data Insights (RDI) remained empirically distinct despite their conceptual relatedness, confirming adequate construct distinctiveness.

RESULTS AND DISCUSSION

Analysis is carried out in a series of systematic steps aiming to ensure good data, good quality of measurement instruments, to explore distributional characteristics of data and to test the three research hypotheses generated from the conceptual framework.

4.1 *Data Screening and Preparation*

The collected responses were pre-screened and prepared for data quality, completeness and suitability for statistical analyses, specifically hierarchical multiple regression analysis, prior to conducting the statistical analyses. Response verification, missing data assessment, outlier examination, reverse coding and preparation of composite variables were conducted as screening procedures. The screening process consisted of an examination of incomplete and duplicate questionnaires, inconsistent response patterns, and missing values. Finally, 320 valid responses were obtained after screening and cleaning the data. This sample size meets the minimum size suggested for hierarchical multiple regression analysis and is large enough to yield medium effect sizes with adequate statistical power.

4.2. *Outlier Assessment*

Outliers were identified by examining standardized z-scores, with values outside the ±3.0 range considered extreme univariate outliers. Specifically, Predictive Intelligence (PI) had a minimum z-score of -2.433 and a maximum score of 1.692; Real-Time Data Insights (RDI) had a minimum z-score of -2.454 and a maximum score of 1.619; Corporate Financial Sustainability (CFS) had a minimum z-score of -2.358 and a maximum score of 1.542; Organizational Factors (OF) had a minimum z-score of -2.550 and a maximum score of 1.564; Industry Factors (IF) had a minimum z-score of -2.051 and a maximum score of 1.893; and AI-Related Risk Factors (AR) had a minimum z-score of -1.904 and a maximum score of 1.809. All of these results support the conclusion that there are no extreme univariate outliers in the data.

Table 2: Outlier Assessment using Z-scores

Variables	Minimum Z-score	Maximum Z-score	Interpretation
Predictive Intelligence (PI)	-2.433	1.692	No severe outliers
Real-Time Data Insights (RDI)	-2.454	1.619	No severe outliers
Corporate Financial Sustainability (CFS)	-2.358	1.542	No severe outliers
Organizational Factors (OF)	-2.550	1.564	No severe outliers
Industry Factors (IF)	-2.051	1.893	No severe outliers
AI-Related Risk Factors (AR)	-1.904	1.809	No severe outliers

DOI: 10.46121/pspc.54.3.33

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4.3. Reverse Coding and Composite Variable Preparation

For this study, the negatively worded item in the Real-Time Data Insights (RDI) scale (Item RDI6) was reverse coded to make it more consistent with the rest of the scale, which indicated that a higher rating would signify greater real-time data insight capabilities. After reverse coding, the composite mean scores for each of the six study constructs were calculated. In quantitative research, composite means are commonly used as they generate stable and representative indicators of each latent construct. All subsequent descriptive statistics, correlation analysis, and hierarchical multiple regression analysis in this chapter were based upon these composite scores.

4.4 Demographic Characteristics

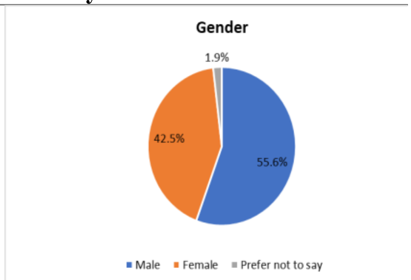
The demographic profile of the 320 respondents includes gender, age group, job position, years of experience in the job, AI/analytics usage, duration of AI/analytics usage, and industry sector.

4.4.1 Gender

The majority of the sample were males (n = 178, 55.6%) followed by females (n = 136, 42.5%) and those who did not specify gender (n = 6, 1.9%). The male preponderance in the gender distribution is consistent with the ratio seen in medium and large organizations in corporate finance and analytics, which has historically been slightly more male. The meaningful representation of women respondents (42.5%) is also an indication of growing gender diversity in finance-related and analytics-oriented professional settings.

Table 3: Demographic Profile of Respondents by Gender

Gender	Frequency	Percentage (%)
Male	178	55.6
Female	136	42.5
Prefer not to say	6	1.9
Total	320	100.0

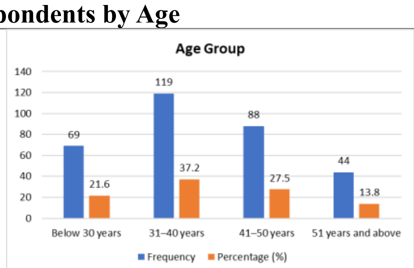


4.4.2 Age

From Table 4, the age distribution of the respondents showed that the age of 31 - 40 (n = 119, 37.2%) had the highest number, followed by 41 - 50 (n = 88, 27.5%). The proportion of respondents under 30 years of age was 21.6% (n = 69) and the age group 51 years and older was 13.8% (n = 44). The age profile is especially relevant to this study as, over the past number of years, professionals aged 31 to 50 are likely to have been directly involved with adopting, implementing and evaluating AI and analytics systems in their organizations.

Table 4: Demographic Profile of Respondents by Age

Age Group	Frequency	Percentage (%)
Below 30 years	69	21.6
31–40 years	119	37.2
41–50 years	88	27.5
51 years and above	44	13.8
Total	320	100.0



4.4.3 Job Position

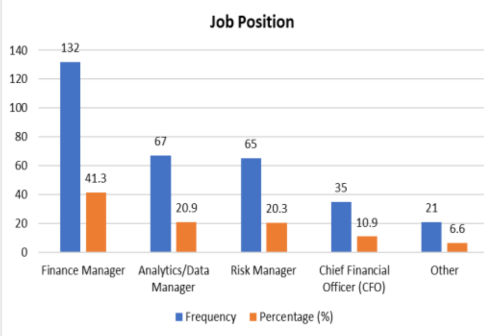
The number of respondents according to their job position is shown in Table 5. The most common occupation was Finance Managers (n = 132, 41.3%), twenty percent (n = 67) of the sample were Analytics or Data Managers, and 20.3% (n = 65) were Risk Managers. Chief Financial Officers (CFOs) accounted for 10.9% (n = 35) and the rest were in other financial and managerial positions (6.6%, n = 21).The mix of the respondents, who hold positions in finance management, data management, data analytics, and executive financial leadership, is suitable to the objectives of the study as they are likely to have first-hand and hands-on experience.

DOI: [10.46121/pspc.54.3.33](https://doi.org/10.46121/pspc.54.3.33)

ISSN:1674-3415

Table 5: Demographic Profile of Respondents by Job Position

Job Position	Frequency	Percentage (%)
Finance Manager	132	41.3
Analytics/Data Manager	67	20.9
Risk Manager	65	20.3
Chief Financial Officer (CFO)	35	10.9
Other	21	6.6
Total	320	100.0

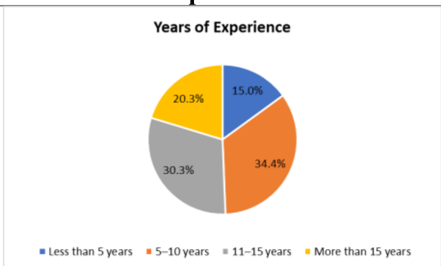


4.4.4 Years of Experience

Table 46 shows the respondents' distribution based on professional experiences which indicated that majority of the respondents (n = 110, 34.4%) had professional experiences ranging from 5 to 10 years, while the second largest group (n = 97, 30.3%) had professional experiences ranging from 11 to 15 years. About 20.3% (n = 65) of the respondents had over 15 years of professional experience and 15.0% (n = 48) had less than 5 years of professional experience.

Table 6: Demographic Profile of Respondents by Professional Experience

Years of Experience	Frequency	Percentage (%)
Less than 5 years	48	15.0
5–10 years	110	34.4
11–15 years	97	30.3
More than 15 years	65	20.3
Total	320	100.0

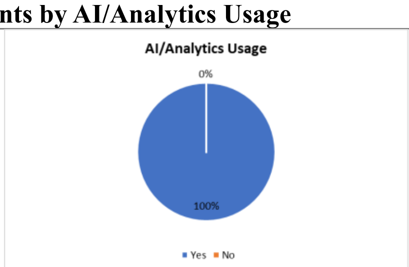


4.4.5 AI/Analytics Usage

Table 7 shows that all 320 respondents (100.0%) said that they actively use AI or analytics systems in their organizations. None of the respondents indicated that such systems were not available, a result of the eligibility criterion used during the data screening process. The significance of this uniform use of AI and analytics tools throughout the sample is that it reflects first-hand experience in the use of the technologies at the heart of the study's research questions.

Table 7: Demographic Profile of Respondents by AI/Analytics Usage

AI/Analytics Usage	Frequency	Percentage (%)
Yes	320	100.0
No	0	0.0
Total	320	100.0



100% of the 320 respondents (no respondents indicated otherwise) reported using AI or analytics systems in their organization. The support for this “unanimous adoption” is a direct result of the eligibility criterion applied during the data screening phase that included ONLY professionals working in medium or large companies that actively use AI or analytics systems for financial decision making.

4.4.6. Industry Sector

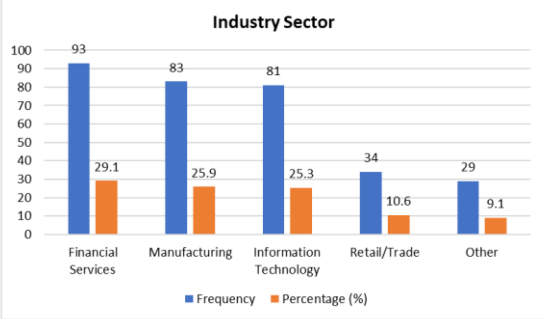
The industry distribution of the respondents is presented in Table 8. Financial Services was the largest sector (n = 93, 29.1%), followed by Information Technology (n = 81, 25.3%) and Manufacturing (n = 83, 25.9%). Ten percent (n = 34) of the sample came from Retail and Trade organizations, and another nine percent (n = 29) came

DOI: 10.46121/pspc.54.3.33

from other organizations. The sector distribution shows that there was some meaningful diversity in the sample as it represents 4 key industry groups. The Financial Services sector is one of the most intense users of AI-driven analytics for financial decision-making and sustainability assessment.

Table 2: Demographic Profile of Respondents by Industry Sector

Industry Sector	Frequency	Percentage (%)
Financial Services	93	29.1
Manufacturing	83	25.9
Information Technology	81	25.3
Retail/Trade	34	10.6
Other	29	9.1
Total	320	100.0



4.5 Descriptive Statistics

Table 9 lists descriptive statistics for all six of the study constructs, of the primary variables of interest, Real-Time Data Insights (RDI) had the highest mean score (M = 3.41, SD = 0.982), followed by Corporate Financial Sustainability (CFS) with a mean of 3.42 (SD = 1.026) and Predictive Intelligence (PI) with a mean score of 3.36 (SD = 0.970). Average-to-high perception ratings across PI, RDI, and CFS show co-movement, indicating that enhanced analytical skills are perceived as connected to increased financial sustainability.

Among control variables showed that the highest mean was for Organizational Factors (OF) with a mean score of 3.48 (SD = 0.972), The responses that organizational factors, such business size and managerial quality, had an impact on financial performance ranged from modest to high. Industry Factors (IF) showed a lower mean score of 3.08 (SD = 1.014) and AI-Related Risk Factors (AR) had the lowest mean score of all the data (M = 3.05, SD = 1.078). Respondents viewed industry dynamics and AI-related risks as relevant but less influential on financial sustainability than organizational factors and analytics capabilities (PI and RDI). The standard deviations were similar for each of the constructs ranging from about 0.97 to 1.08, indicating moderate dispersion in the perceptions of the respondents. The min values of 1.00 and the max values of 5.00 for all the constructs show that the respondents used the entire scale of the Likert, again demonstrating the discriminant quality of the measurement instrument.

Table 3: Descriptive Statistics for all Variables (N = 320)

Construct	Minimum	Maximum	Mean	Std. Deviation
Predictive Intelligence (PI)	1.00	5.00	3.36	0.970
Real-Time Data Insights (RDI)	1.00	5.00	3.41	0.982
Corporate Financial Sustainability (CFS)	1.00	5.00	3.42	1.026
Organizational Factors (OF)	1.00	5.00	3.48	0.972
Industry Factors (IF)	1.00	5.00	3.08	1.014
AI-Related Risk Factors (AR)	1.00	5.00	3.05	1.078

4.6. Normality Analysis

Data distributions were checked for normality using skewness and kurtosis coefficients for all six constructs. These statistics offer valuable insights in the data distributions and whether they are appropriate for parametric statistical analyses such as hierarchical multiple regression. The skewness of all constructs as reported in Table 10 were moderate and within acceptable limits. PI had a skewness of -0.314, which had a slight negative value and was consistent with a mild tendency for responses to cluster towards the higher scale values. The skewness value for Real-Time Data Insights (RDI) was -0.263 and for Corporate Financial Sustainability (CFS) was -0.195, which was the closest to 0 among the three major constructs. The skewness statistics for the control variables resulted in a skewness of -0.367 for Organizational Factors (OF), 0.044 for Industry Factors (IF) (which is almost zero), and 0.005 for AI-Related Risk Factors (AR), which is very near to zero. All constructs had a negative kurtosis value, which indicated a platykurtic distribution, and a slightly flatter profile than a standard normal distribution. The kurtosis for PI was -0.557, for RDI -0.791, and for CFS -0.970. The control variables had a kurtosis of -0.610 for OF, -0.751 for IF, and the most extreme of all at -0.890 for AR.

DOI: 10.46121/pspc.54.3.33

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Table 4: Normality Assessment

Construct	Skewness	Kurtosis
Predictive Intelligence (PI)	-0.314	-0.557
Real-Time Data Insights (RDI)	-0.263	-0.791
Corporate Financial Sustainability (CFS)	-0.195	-0.970
Organizational Factors (OF)	-0.367	-0.610
Industry Factors (IF)	0.044	-0.751
AI-Related Risk Factors (AR)	0.005	-0.890

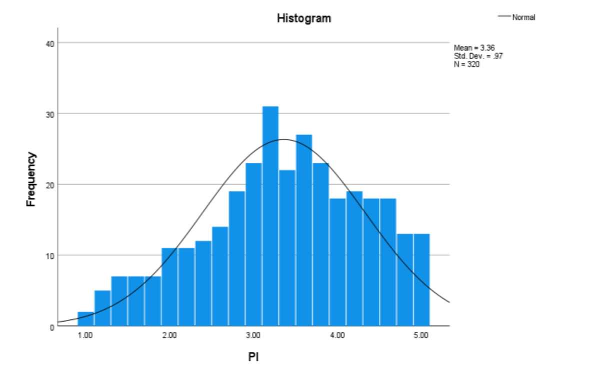

Figure 2: Histogram for PI.

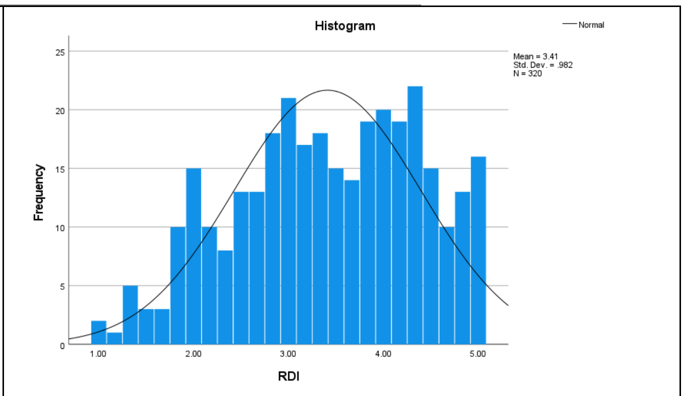

Figure 3: Histogram for RDI.

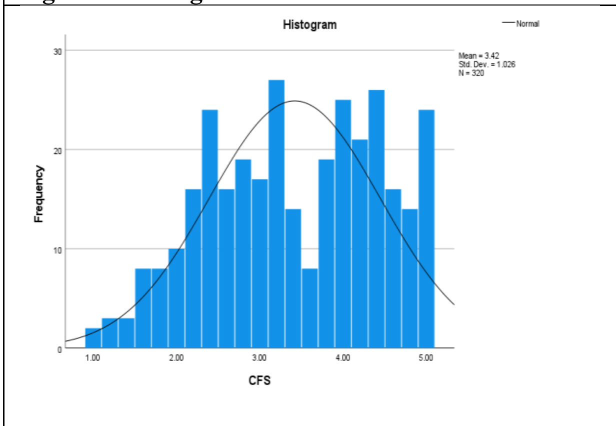

Figure 4: Histogram for CFS

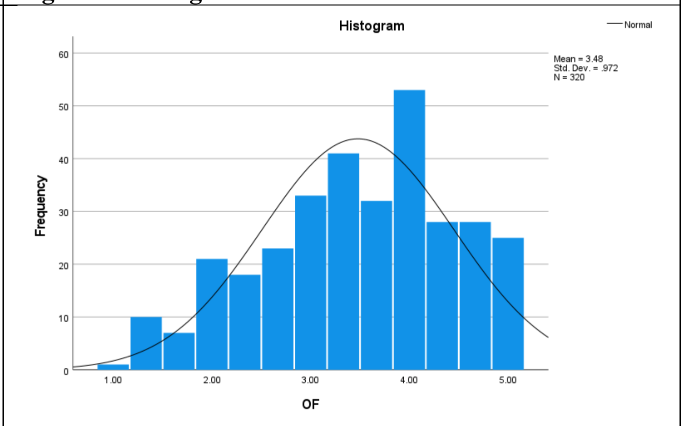

Figure : Histogram for OF

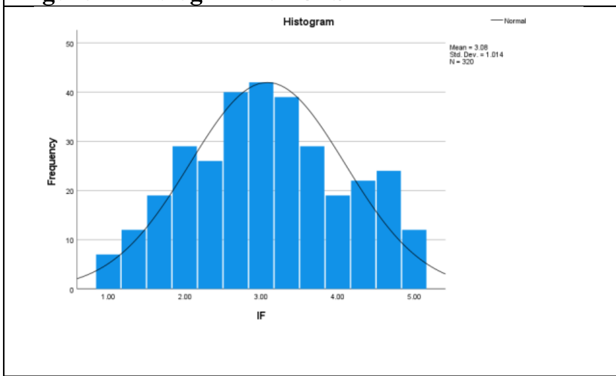

Figure 6: Histogram for IF

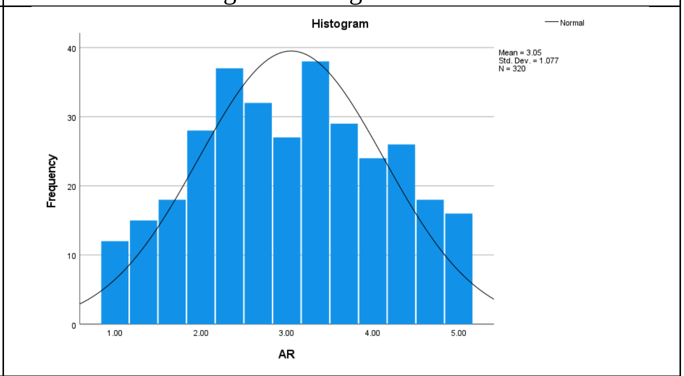

Figure 7: Histogram for AR

4.7 Reliability and Validity Analysis

4.7.1 Reliability Analysis

Each of the six study constructs had good internal consistency reliability as presented in Table 11. Three constructs namely Predictive Intelligence (PI, 5 items), Corporate Financial Sustainability (CFS, 5 items) and Real-Time Data Insights (RDI, 6 items) had excellent Cronbach's Alpha value which was 0.902, 0.909 and 0.915 respectively. Similarly, the control variable scales showed good reliability with Organizational Factors (OF) having a value of

DOI: 10.46121/pspc.54.3.33

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0.845, Industry Factors (IF) 0.848 and AI-Related Risk Factors (AR) 0.859. All values fall within a range that was widely accepted as 0.70, demonstrating the psychometric soundness of the measurement instrument, which would afford confidence in the subsequent validity assessments and regression analyses.

Table 5: Reliability Analysis using Cronbach's Alpha

Construct	Number of Items	Cronbach's Alpha	Interpretation
Predictive Intelligence (PI)	5	0.902	Excellent
Real-Time Data Insights (RDI)	6	0.915	Excellent
Corporate Financial Sustainability (CFS)	5	0.909	Excellent
Organizational Factors (OF)	3	0.845	Good
Industry Factors (IF)	3	0.848	Good
AI-Related Risk Factors (AR)	3	0.859	Good

4.7.2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were used to determine the suitability of the data set for factor analysis. The KMO measure of sampling adequacy was 0.895, which is greater than the recommended value of 0.60 (Table 12); this is classified as meritorious to excellent. This value shows that the percentage of variance of the variables attributed to the common underlying factors is high and it is evident that the correlation structure of the data is appropriate for factor analysis. An approximate chi-square value of 4711.776 with 300 degrees of freedom was obtained in Bartlett's Test of Sphericity, which was significant ($p = 0.000$). This output provides a test of the hypothesis that the correlation matrix is an identity matrix, thus indicating that there are enough intercorrelations among the variables to recommend further analysis by factor analysis.

Table 6: KMO and Bartlett's Test

Test	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.895
Bartlett's Test Approx. Chi-Square	4711.776
Degrees of Freedom (df)	300
Significance (p-value)	0.000

4.7.3 Construct Validity

For the primary constructs, loadings for the items ranged from 0.779 to 0.805 for PI, 0.791 to 0.831 for RDI, and 0.784 to 0.812 for CFS, all demonstrating strong and consistent alignment of items to their respective constructs. Control variables included OF loading between 0.831 and 0.846, with the highest item-level loadings in the study being with IF between 0.858 and 0.893, and AR ranged from 0.861 to 0.891. The consistent high factor loadings across all constructs, along with reliability results, it indicate the psychometric soundness of the measurement instrument and lend confidence in the validity of the data for subsequent regression analysis.

Table 7: Construct Validity based on Factor Loadings

Construct	Item	Factor Loadings
Predictive Intelligence (PI)	PI1	0.805
	PI2	0.804
	PI3	0.792
	PI4	0.788
	PI5	0.779
Real-Time Data Insights (RDI)	RDI1	0.797
	RDI2	0.806
	RDI3	0.797
	RDI4	0.831
	RDI5	0.824
	RDI6	0.791
Corporate Financial Sustainability (CFS)	CFS1	0.807
	CFS2	0.811
	CFS3	0.784

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	CFS4	0.801
	CFS5	0.812
Organizational Factors (OF)	OF1	0.844
	OF2	0.831
	OF3	0.846
Industry Factors (IF)	IF1	0.893
	IF2	0.858
	IF3	0.868
AI-Related Risk Factors (AR)	AR1	0.884
	AR2	0.891
	AR3	0.861

4.8. Common Method Bias

Harman's Single Factor Test was used to evaluate common method bias (CMB) in this cross-sectional dataset. A first factor with an eigenvalue of 7.656 from the principal component analysis explained 30.625% of the overall variance, which is significantly less than the 50% threshold that indicates substantial CMB. This results implies that the validity of the study's conclusions is not seriously threatened by common method bias. These results give reasonable assurance that the results in the following analyses are indeed construct-level relationships and not artefacts of common method variance. The low level of shared variance captured by the first factor also provides further evidence of the discriminant quality of the measurement scales identified in the construct validation analysis and adds to confidence in the integrity of the data.

Table 8: Common Method Bias Assessment using Harman's Single Factor Test

Component	Initial Eigenvalue	Percentage of Variance Explained (%)	Cumulative Percentage (%)
Factor 1	7.656	30.625	30.625

4.9. Correlation Analysis

All variables had adequate correlations, according to Pearson correlation analysis (Table 15). Predictive Intelligence (PI: $r = 0.476$, $p < 0.01$) and Real-Time Data Insights (RDI: $r = 0.417$, $p < 0.01$) were the two main predictors that demonstrated substantial positive relationships with Corporate Financial Sustainability (CFS), offering preliminary support for H1 and H2. RD and PIThey had a moderate correlation with one another ($r = 0.436$, $p < 0.01$), which is indicative of their similar analytical skills. Industry Factors (IF) showed the lowest positive link ($r = 0.113$, $p < 0.05$) with CFS among controls, whereas Organizational Factors (OF) had the greatest ($r = 0.366$, $p < 0.01$). CFS and AI-Related Risks (AR) had a substantial negative connection ($r = -0.125$, $p < 0.05$). In keeping with VIF diagnostics, no inter-predictor correlations were more than 0.80, suggesting no multicollinearity issues.

Table 9: Correlation Matrix

Variables	PI	RDI	CFS	OF	IF	AR
Predictive Intelligence (PI)	1					
Real-Time Data Insights (RDI)	0.436**	1				
Corporate Financial Sustainability (CFS)	0.476**	0.417**	1			
Organizational Factors (OF)	0.369**	0.163**	0.366**	1		
Industry Factors (IF)	0.014	0.033	0.113*	0.053	1	
AI-Related Risk Factors (AR)	0.080	0.036	-0.125*	0.010	0.022	1

Note: **p < 0.01, *p < 0.05

4.10. Data Analysis for Research Objective 1

Research Objective 1 was to look at Predictive Intelligence (PI) and its effect on Corporate Financial Sustainability (CFS). The hypothesis, Research Hypothesis 1 (H1), that was associated with the study was that Predictive Intelligence positively affects the Corporate Financial Sustainability. To test this hypothesis a hierarchical multiple regression analysis was used in two steps. In the first step (Model 1), each of the three control variables (Organizational Factors (OF), Industry Factors (IF), AI-Related Risk Factors (AR)) was simultaneously entered to determine the baseline explanatory variance where control variables accounted for the effects alone. Predictive Intelligence (PI) was introduced as a second step (Model 2) to evaluate its added value beyond the controls.

Hypotheses 1 (H1): Predictive Intelligence positively influences Corporate Financial Sustainability.

DOI: 10.46121/pspc.54.3.33

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ISSN:1674-3415

Hierarchical multiple regression analysis was conducted to examine the influence of Predictive Intelligence (PI) on Corporate Financial Sustainability (CFS) after controlling for Organizational Factors (OF), Industry Factors (IF), and AI-Related Risk Factors (AR).

Model 1: Control Variables:
With $R = 0.400$, $R^2 = 0.160$, and adjusted $R^2 = 0.152$, Model 1, which included three control variables, was statistically significant ($F(3, 316) = 20.020$, $p < 0.001$), suggesting that controls accounted for 16% of the variation in Corporate Financial Sustainability (CFS). There was no autocorrelation, according to the Durbin-Watson statistic (1.983). AI-Related Risks (AR) had a significant negative effect ($\beta = -0.131$, $p = 0.011$), Industry Factors (IF) had a positive but marginally non-significant effect ($\beta = 0.097$, $p = 0.061$), and Organizational Factors (OF) had the strongest positive effect ($\beta = 0.362$, $p < 0.001$). No multicollinearity was established by VIF values.

Table 10: Model Summary for Control Variables

Model	R	R²	Adjusted R²	Std. Error	F	Sig.	Durbin-Watson
Model 1	0.400	0.160	0.152	0.9446	20.020	0.000	1.983

Table 11: ANOVA for Control Variables

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	53.594	3	17.865	20.020	0.000
Residual	281.974	316	0.892		
Total	335.568	319			

Table 18: Coefficients for Control Variables

Predictor	B	Beta (β)	t-value	Sig.	VIF
OF	0.382	0.362	7.006	0.000	1.214
IF	0.098	0.097	1.877	0.061	1.107
AR	-0.125	-0.131	-2.543	0.011	1.089

Model 2: Effect of Predictive Intelligence (PI):
With a substantial ΔR^2 of 0.144 (F Change = 65.235, $p < 0.001$) and an increase in R^2 to 0.304 in Model 2, the addition of Predictive Intelligence (PI) considerably improved model fit and explained an extra 14.4% of the variation in CFS beyond controls. PI showed a significant favorable impact ($\beta = 0.410$, $p < 0.001$). IF became significant ($\beta = 0.100$, $p = 0.035$), AR remained adversely linked with CFS ($\beta = -0.162$, $p = 0.001$), and OF remained substantially positive ($\beta = 0.211$, $p < 0.001$) among controls; VIF values (1.142–1.846) revealed no multicollinearity. These results demonstrate the significant positive impact of PI on Corporate Financial Sustainability and provide strong support for Research Hypothesis 1.

Table 12: Model Summary for Predictive Intelligence

Model	R	R²	Adjusted R²	ΔR²	Std. Error	F Change	Sig.	Durbin-Watson
Model 2	0.551	0.304	0.295	0.144	0.8611	65.235	0.000	2.031

Table 13: ANOVA for Predictive Intelligence

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	101.971	4	25.493	34.376	0.000
Residual	233.597	315	0.742		
Total	335.568	319			

Table 14: Coefficients for Predictive Intelligence

Predictor	B	Beta (β)	t-value	Sig.	VIF
OF	0.222	0.211	4.161	0.000	1.384
IF	0.101	0.100	2.121	0.035	1.214
AR	-0.155	-0.162	-3.444	0.001	1.142
PI	0.434	0.410	8.077	0.000	1.846

DOI: 10.46121/pspc.54.3.33

4.11 Data Analysis for Research Objective 2

Research Objective 2 was to understand the impact of Real-Time Data Insights (RDI) in improving Corporate Financial Sustainability (CFS). The related Research Hypothesis 2 (H2) stated that Real-Time Data Insights have a positive impact on Corporate Financial Sustainability. To test this hypothesis, a hierarchical multiple regression analysis was performed, with the same control variable baseline as that of Model 1 (Section 4.9). To account for the unique contribution of Real-Time Data Insights (RDI), the variable was added in a separate regression step (Model 3) to explain variance in CFS above and beyond the control variables.

Hypotheses 2 (H2): Real-Time Data Insights positively influence Corporate Financial Sustainability.
Hierarchical multiple regression analysis was conducted to examine the influence of Real-Time Data Insights (RDI) on Corporate Financial Sustainability (CFS) after controlling for OF, IF, and AR.

Model 3: Effect of Real-Time Data Insights (RDI):
Though Real-Time Data Insights (RDI) was included to Model 3, R^2 increased to 0.293 ($\Delta R^2 = 0.133$, F Change $= 59.300$, $p < 0.001$), and RDI had a significant positive impact on CFS ($\beta = 0.370$, $p < 0.001$). Only Organizational Factors (OF) was substantially positive ($\beta = 0.302$, $p < 0.001$) among controls; Industry Factors (IF) was not significant ($p = 0.064$); and AI-related Risks (AR) continued to be significantly negative ($\beta = -0.144$, $p = 0.003$). No multicollinearity was established by VIF values (1.121–1.731). Research Hypothesis 2 was fully supported by the comparable and complementary contributions of PI ($\Delta R^2 = 0.144$, $\beta = 0.410$) and RDI ($\Delta R^2 = 0.133$, $\beta = 0.370$) to the explanation of CFS.

Table 15: Model Summary for Real-Time Data Insights

Model	R	R^2	Adjusted R^2	ΔR^2	Std. Error	F Change	Sig.	Durbin-Watson
Model 3	0.541	0.293	0.284	0.133	0.8679	59.300	0.000	2.050

Table 16: ANOVA for Real-Time Data Insights

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	98.267	4	24.567	32.611	0.000
Residual	237.301	315	0.753		
Total	335.568	319			

Table 17: Coefficients for Real-Time Data Insights

Predictor	B	Beta (β)	t-value	Sig.	VIF
OF	0.318	0.302	6.280	0.000	1.276
IF	0.089	0.088	1.860	0.064	1.203
AR	-0.137	-0.144	-3.033	0.003	1.121
RDI	0.387	0.370	7.701	0.000	1.731

4.12 Data Analysis for Research Objective 3

The goal of the research Objective 3 was to assess the joint contribution of Predictive Intelligence (PI) and Real-Time Data Insights (RDI) towards Corporate Financial Sustainability (CFS). Research Hypothesis 3 (H3) assumed that both Predictive Intelligence and Real-Time Data Insights contribute to a significant variance in Corporate Financial Sustainability. This hypothesis was tested using a hierarchical multiple regression analysis in which both PI and RDI were added to the model one step at a time with the three control variables (OF, IF, AR) (Model 1).

Hypotheses 3 (H3): Predictive Intelligence and Real-Time Data Insights jointly explain significant variance in Corporate Financial Sustainability.

Hierarchical multiple regression analysis was conducted to examine the combined explanatory contribution of Predictive Intelligence (PI) and Real-Time Data Insights (RDI) to Corporate Financial Sustainability (CFS) after controlling for OF, IF, and AR.

DOI: 10.46121/pspc.54.3.33

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ISSN:1674-3415

4.12.1 Model 4: Combined Explanatory Contribution of PI and RDI

In addition to R = 0.597 and $R^2 = 0.357$, the combined model (PI, RDI, and control variables) in Model 4 explained 35.7% of the variation in Corporate Financial Sustainability (CFS). PI and RDI simultaneously explained 19.7% more variation than controls, according to the ΔR^2 of 0.197, a statistically significant increase (F Change = 48.044, $p < 0.001$). Model fit and lack of autocorrelation are confirmed by adjusted R2 = 0.346 and Durbin-Watson = 2.051.

Model 4 explained 35.7% of the variance in Corporate Financial Sustainability (CFS) and was statistically significant ($F(5, 314) = 34.806$, $p < 0.001$). Real-Time Data Insights (RDI: $\beta = 0.255$, $p < 0.001$) and Predictive Intelligence (PI: $\beta = 0.299$, $p < 0.001$) both demonstrated substantial positive benefits, demonstrating their unique and autonomous contributions. AI-related risks (AR: $\beta = -0.163$, $p < 0.001$) had a substantial negative impact, although organizational factors (OF: $\beta = 0.210$, $p < 0.001$) and industry factors (IF: $\beta = 0.093$, $p = 0.041$) were also beneficial. No multicollinearity was established by VIF values (< 2). The synergy between the two constructs was demonstrated by the combined ΔR^2 of 0.197, which was higher than the separate ΔR^2s (PI: 0.144; RDI: 0.133). Research Hypothesis 3 is fully supported by the combination of PI and RDI, which offer a more thorough explanation of financial sustainability than each statistic individually.

Table 18: Model Summary for Combined Explanatory Contribution

Model	R	R^2	Adjusted R^2	ΔR^2	Std. Error	F Change	Sig.	Durbin-Watson
Model 4	0.597	0.357	0.346	0.197	0.8292	48.044	0.000	2.051

Table 19: ANOVA for Combined Explanatory Contribution

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	119.663	5	23.933	34.806	0.000
Residual	215.905	314	0.688		
Total	335.568	319			

Table 20: Coefficients for Combined Explanatory Contribution

Predictor	B	Beta (β)	t-value	Sig.	VIF
OF	0.222	0.210	4.314	0.000	1.492
IF	0.094	0.093	2.052	0.041	1.238
AR	-0.155	-0.163	-3.582	0.000	1.174
PI	0.316	0.299	5.578	0.000	1.982
RDI	0.267	0.255	5.073	0.000	1.864

4.12.2 Supplementary Regression Assumption Testing

Further regression diagnostic tests were performed to determine if the data were appropriate for hierarchical multiple regression analysis. Multi-collinearity, autocorrelation, homoscedasticity, linearity and normality of the residuals based on the final regression model were assessed as diagnostic procedures. A full set of regression diagnostic tests were carried out on the final model (Model 4) to ensure the statistical integrity and interpretability of the results of the hierarchical multiple regression. The diagnostic procedures used to evaluate the key assumptions of multiple regression analysis were multicollinearity, auto-correlation, homoscedasticity, linearity, and normality of residuals.

4.12.2.1 Multicollinearity Assessment

Variance Inflation Factor (VIF) values were calculated and used to check for multicollinearity. All the VIF values were lying between 1.174 and 1.982 and were well below the recommended value of 5.0. The results show that there is no multicollinearity problem between the predictor variables.

4.12.2.2 Autocorrelation Assessment

Durbin–Watson test was used to check autocorrelation. The Durbin–Watson values for the regression models varied between 1.983 and 2.051, which showed that there were no autocorrelation problems in the regression residuals.

4.12.2.3 Homoscedasticity and Linearity Assessment

A graph of the standardized predicted values (ZPRED) versus standardized residuals (ZRESID) was used to assess the assumptions of homoscedasticity and linearity. There were no funnel-shaped or curved patterns in the scatterplot and the residuals were randomly and evenly distributed about zero. The results showed that the assumptions of homoscedasticity and linearity were reasonably fulfilled.

4.12.2.4 Normality of Residuals

Histogram analysis and normal probability (P-P) plots were used to evaluate the normality of the residuals. The regression standardized residual histogram was mostly bell-shaped and the regression P-P plot showed that the points were close to the diagonal reference line with a few minor deviations. These results suggest that the normality assumption of the residuals was acceptable.

4.13 Summary of Hypothesis Testing

The results of the hierarchical multiple regression analyses (Table 28) give clear support to all three research hypotheses. H1 is supported, and PI is found to have a strong positive impact on CFS ($\beta = 0.410$, $t = 8.077$, $p < 0.001$, $\Delta R^2 = 0.144$), which means that the predictive analytics capabilities are a valuable factor that can positively influence the corporate financial sustainability in accordance with the RBV and Dynamic Capability Theory.

Table 21: Hypotheses Testing

Hypothesis	Statement	Statistical Evidence	Decision
H1	Predictive Intelligence (PI) positively influences Corporate Financial Sustainability (CFS).	$\beta = 0.410$, $t = 8.077$, $p < 0.001$	Supported
H2	Real-Time Data Insights (RDI) positively influence Corporate Financial Sustainability (CFS).	$\beta = 0.370$, $t = 7.701$, $p < 0.001$	Supported
H3	Predictive Intelligence (PI) and Real-Time Data Insights (RDI) jointly explain significant variance in Corporate Financial Sustainability (CFS).	PI: $\beta = 0.299$, $t = 5.578$, $p < 0.001$; RDI: $\beta = 0.255$, $t = 5.073$, $p < 0.001$; $\Delta R^2 = 0.197$	Supported

Results showed that H2 is also fully supported, as RDI had a significant positive effect on CFS ($\beta = 0.370$, $t = 7.701$, $p < 0.001$, $\Delta R^2 = 0.133$), indicating that the data insight capability of real-time data has a significant positive influence on financial sustainability, as viewed from the DDDM perspective and Dynamic Capability Theory. H3 was also supported, as PI ($\beta = 0.299$, $p < 0.001$) and RDI ($\beta = 0.255$, $p < 0.001$) both still had significant positive effects when used in combination (joint $\Delta R^2 = 0.197$, F Change = 48.044, $p < 0.001$), confirming the complementary and synergistic effects of both on financial sustainability outcomes. In every model, OF was a significant positive predictor of CFS, while IF was marginally significant and positive and AR was a significant negative predictor, highlighting the need for strong AI governance structures in addition to technological investments.

CONCLUSION

This study examine the impact of Predictive Intelligence (PI) and Real-Time Data Insights (RDI) on Corporate Financial Sustainability (CFS), while controlling for organizational factors, industry factors, and AI-related risk factors. Drawing on the Resource-Based View (RBV), Dynamic Capability Theory, and the Data-Driven Decision-Making (DDDM) perspective, the study developed a conceptual framework proposing that PI and RDI as distinct but complementary analytic capabilities positively influence CFS both individually and jointly.

Corporate Financial Sustainability (CFS) benefits greatly from Predictive Intelligence (PI), which confirms that forward-looking analytics capabilities improve forecasting accuracy, risk anticipation, and strategic financial planning. Additionally, CFS benefits greatly from Real-Time Data Insights (RDI), which shows that the ability to access and act upon current data supports continuous monitoring, quick response, and financial stability. Significant variation in CFS is jointly explained by PI and RDI, and when combined, both variables maintain strong independent effects. This confirms their complementary and synergistic contributions to financial sustainability outcomes. Among the control variables, Organizational Factors (OF) consistently showed a strong positive effect on CFS across all models, while Industry Factors (IF) demonstrated a positive but weaker and

DOI: 10.46121/pspc.54.3.33

sometimes marginally significant effect. Importantly, AI-Related Risk Factors (AR) consistently exhibited a significant negative relationship with CFS, underscoring the need for robust AI governance, data quality management, and careful mitigation of risks such as overreliance on AI, alert fatigue, and data quality issues.

The findings have several theoretical implications. Through recognizing PI and RDI as separate strategic skills rather than merely technical tools, each of which contributes differently to company performance, they first expand the RBV. Second, by demonstrating that RDI promotes seizing and reconfiguration (allowing quick reaction to changing conditions) and PI improves organizational sensing (identifying future patterns and hazards), they strengthen Dynamic Capability Theory. Third, they support the DDDM viewpoint by showing how real-time and forward-looking analytics enhance the speed, confidence, and quality of financial management decisions. Practically speaking, though, the findings provide enterprises looking to use AI-enabled data for financial sustainability with unambiguous recommendations. To build a complete decision-support architecture, real-time data infrastructure should be added to investments in predictive analytic.

Despite its contributions, this study has several limitations. The cross-sectional design limits causal inference, and future research could adopt longitudinal or quasi-experimental approaches to establish causality. The reliance on self-reported perceptual data, while methodologically addressed, could be supplemented with objective financial performance metrics in future studies. Additionally, the sample, though diverse, may not fully represent all industries or geographic regions, and further research could explore sector-specific or cross-cultural variations in the effects of PI and RDI on CFS.

In conclusion, this study provides robust empirical evidence that Predictive Intelligence and Real-Time Data Insights are valuable organizational capabilities that significantly enhance Corporate Financial Sustainability both independently and in combination. Organizations that effectively integrate these analytic capabilities into their financial decision-making processes, while managing associated risks, are better positioned to achieve long-term financial resilience, stability, and sustainable performance in an increasingly data-driven and uncertain business environment.

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