# Integrated AI and Business Intelligence Maturity: Drivers of FP&A Decision Making Quality

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**Abstract.** Business Intelligence (BI) constitutes a suite of technologies that enhance managerial and analytical decision-making, while the integration of Artificial Intelligence (AI) into accounting and finance has expanded considerably in recent years. This study proposes an evaluation framework structured around four critical dimensions—technology, data, processes, and organizational readiness—and applies it through comparative case analyses of Tencent, Lenovo, and Dah Sing Bank. By combining qualitative insights with quantitative assessment, the research empirically demonstrates a positive correlation between AI/BI maturity and the quality of Financial Planning and Analysis (FP&A) outcomes, specifically in prediction accuracy, decision timeliness, scenario and sensitivity analysis, and strategic influence. The results indicate that enterprises with high AI/BI maturity achieve substantial improvements in predictive capability, operational agility, and strategic impact, whereas low-maturity firms remain dependent on traditional spreadsheet-based tools such as Excel, which constrain efficiency and adaptability. The findings contribute to the literature on digital transformation in accounting and finance, while also offering practical guidance for enterprises seeking to optimize FP&A practices through the systematic advancement of AI and BI maturity.

**Keywords:** Business Intelligence, Artificial Intelligence, Financial Planning and Analysis (FP&A), Decision Making Quality.

## 1. Introduction

FP&A works were initially, and still prevailing today, done by utilizing spreadsheets like Excel. Spreadsheets came into the view of public the debut of Microsoft Excel in the 1980s [1]. And nowadays, spreadsheets such as Excel remain dominant, as office workers today still use such tools from time to time to visualize, analyze, organize, share and present slices of corporate data. Artificial Intelligence (AI), the trending computer system with enormous potential in lots of fields of study, is driven by machine learning technologies. They stand out due to their impressive ability in data analysis, pattern-recognition, and decision-making [2]. With the help of AI, FP&A was transformed from a passive and time-consuming process into a dynamic and predictive strategy based on real-time data [3]. AI has grown beyond automating routine bookkeeping and audit tasks to become a critical enabler of strategic financial planning and analysis (FP&A). Technologies such as machine learning, expert systems, and business intelligence (BI) tools now support tasks like forecasting performance trends and modelling cash flow risks. They empower finance functions to offer forward-looking insights and scenario simulations rather than just retrospective reports [4]. However, there are significant differences in the maturity of AI and BI system applications among different enterprises, and how these differences affect the decision quality of FP&A has not been systematically studied [5].

AI in accounting functions is revolutionizing Financial Planning & Analysis (FP&A) fundamentally, bringing major enhancements in the accuracy of forecasts, strategic responsiveness, and decision-making value to enterprises. AI-enabled models, especially machine learning (ML), supplement classic forecasting techniques by aggregating and analyzing immense amounts of structured and unstructured data—such as transactional histories, market and social media sentiment, and macroeconomic signals—to recognize intricate, non-linear patterns frequently invisible to humans or classic statistical software [6, 7]. This function minimizes forecasting mistakes by 20-50% and supports real-time, dynamic updating, in lieu of frozen, annual static budgets, to dynamic, scenario-based forecasts that frequently update to respond to new operational signals [8, 9].AI algorithms, for example, can recalibrate revenue forecasts based on real-time CRM data (e.g., new deals) or revise cost forecasts considering supply chain disturbances, so plans remain synchronized to a company’s current situation [8, 10].

In addition to accuracy, AI increases the strategic value of FP&A through the facilitation of sophisticated causal inference and scenario planning. Such methods as double machine learning decouple cause-and-effect relationships within finance data, enabling organizations to advance past correlation-based forecasts and make resource allocation decisions based on empirical causality [6]. At the same time, AI streamlines the creation and simulation of numerous scenarios, as well as enabling leaders to simulate in advance and make optimal strategy decisions in the face of uncertainty [7, 8]. The transition is accelerated through AI integration into cloud-based FP&A platforms, which consolidate data from ERP, CRM, and BI applications via APIs or ETL pipelines. The result is a consistent "single source of truth," eliminating departmental walls and facilitating cross-divisional collaboration in which sales, operations, and finance jointly own forecasts based on normalized drivers [9, 10].

Integration of operational, financial, and ESG data in AI-operated FP&A systems increases decision-making quality further. AI-based models incorporate sustainability KPIs into financial logics to allow for a whole performance view and ensure that profitability and long-term resilience inform strategic decisions [8]. The unified view, supplemented by AI’s capability to spot anomalies and create prescriptive suggestions, converts finance teams from reporters into strategic counselors able to influence in-real-time course corrections [7, 8]. Decision cycles, as a result, decrease considerably, and resource allocation grows in responsiveness—cloud-based AI FP&A solutions, for instance, cutting data integration times and planning iterations by as much as up to 70% [9]. However, realizing such benefits requires overcoming basic challenges. Data quality, governance, and integration complexity remain barriers, necessitating robust data pipelines and standard KPIs [6, 10]. Model transparency and ethical governance are equally critical; "black box" AI systems can generate distrust, so explainable AI (XAI) methods and human oversight mechanisms become necessary to validate assumptions, ensure regulatory compliance, and prevent bias [7, 8]. Culturally, enterprises must inculcate planning fluency across departmental levels, training non-finance stakeholders to read AI-powered insights and accept continual forecasting mindsets [8]. Ultimately, when implemented strategically—with executive champion, cross-disciplinary collaboration (IT, FP&A, operations), and modularity of architecture—AI takes FP&A to an "autonomous, signal-responsive command center," closing strategic objectives and operational execution gaps and driving enduring enterprise value [7].

Based on the reviews presented previously, this research constructs an AI and BI maturity evaluation model from dimensions of AI and BI initial conditions such as organizational readiness and different aspects of FP&A decision qualities. By obtaining data from different companies, this research aims to analyze the performance of different companies’ FP&A decisions and to give insights on how the maturity of integrated AI and Business Intelligence systems would influence a company’s quality of decision-making in FP&A.

## 2. Research Hypothesis

The evaluation model has independent and dependent variables for further investigation. The independent variable of this research is the levels of AI and BI adoption maturity, and it is split into four specific dimensions: technology, process, data and organizational readiness. Each dimension plays a crucial role in representing the AI and BI adoption maturity. Similarly, the dependent variable is the quality of FP&A decision making quality and it is also split into four dimensions which directly reflect how good the FP&A of a firm is working. They forecast accuracy and frequency, time-to-decision, scenario and sensitivity analysis capability and actionability and strategic impact.

Based on the independent and dependent variables and previous review of literature, the main hypothesis is that there is a positive correlation between AI and BI adoption maturity and FP&A

decision making quality. This is induced from that the maturity of a company's AI and BI incorporation can be separated into three accounting-focused levels, from high to medium to low, in general maturity models.

Firstly, at the high maturity level, organizations possess the ability to harness advanced predictive analytics, create automated dashboards, and run scenario simulation tools as part of their FP&A toolkit. Such firms typically use AI-powered models—like machine learning or time-series forecasting—to analyze large and complex historical and external datasets, delivering high predictive accuracy and strategic foresight [2]. These tools empower finance teams to run real-time "what-if" simulations, stress-test assumptions against market shifts, and quickly adapt plans based on new information. Dashboards in these organizations are not static; they automatically update, visualize key financial metrics, and provide alerts or insights—enabling decision-makers to quickly identify trends, anomalies, or emerging risks [11]. For instance, leading firms deploy interactive executive dashboards that integrate multiple data sources—such as ERP, CRM, and external economic indicators—providing a unified, real-time view of revenue, cash flow, and KPIs. These dashboards support strategic discussions at the board level and empower leadership to respond proactively [12]. Collectively, this rich combination of predictive modeling, dynamic visualizations, and simulation capabilities marks high maturity FP&A functions—where AI transitions the role from retrospective reporting to strategic advising, enabling more confident, evidence-based financial decisions.

Secondly, at the medium maturity level, organizations have typically adopted Business Intelligence (BI) tools—such as Power BI, Qlik, or similar platforms—to enhance budgeting and variance analysis—but still rely on partially manual processes. For example, finance teams may automate dashboards and reports that highlight variances between actual and budgeted figures, enabling more data-informed reviews. They still, however, perform significant manual follow-up to interpret those variances, integrate departmental inputs, and finalize planning decisions. Recent studies emphasize that variance analysis at this stage remains a semi-automated process, where BI triggers alerts or visualizations, but human analysts still conduct root-cause investigation and make final recommendations [13]. While driver-based budgeting supported by BI boosts tactical agility, driver cascades and full scenario simulations often depend on manual adjustments or offline models. This combination of automated reporting and manual intervention characterizes medium maturity: it delivers improved visibility and positional clarity, yet stops short of fully AI-driven, predictive or prescriptive financial planning workflows. Business Intelligence supports the process, but human oversight remains integral to decision-making.

Lastly, when a company operates at a low maturity level in AI or Business Intelligence (BI), its finance and accounting systems often remain tightly bound to Excel spreadsheets and other legacy tools. Spreadsheets, while popular and familiar, introduce significant challenges—multiple, conflicting versions of data, manual aggregation, and no single source of truth—which directly undermine the integrity and scalability of financial analysis [14]. Because the data is scattered and inconsistent, AI tools struggle to function effectively—sometimes leading to the "garbage in, garbage out" issue, where flawed inputs result in unreliable outputs [14]. In this environment, AI usage is minimal—the finance team lacks meaningful automation and predictive capabilities. As a result, forecasting remains retrospective and descriptive, rather than forward-looking, and any strategic insights are limited to basic human-driven reviews rather than AI-supported scenario modelling. Unlike organizations at higher maturity levels—which employ automated dashboards, real-time forecasting, and advanced simulation tools—low maturity firms often have only manual, post-hoc reporting. Their financial forecasting lacks predictive sophistication, relies heavily on human judgment, and does not support agile decision-making. The pervasive use of legacy spreadsheets signifies reduced capability to enable predictive strategic advising, as the infrastructure and culture needed to support AI-enabled FP&A simply aren't in place.

For further investigation on the impact of specific dimensions of the independent variables, four sub hypotheses, from H1 to H4, are stated.

Hypothesis 1 (H1): higher technology level would help to increase forecast accuracy and frequency to FP&A decision making quality.

Hypothesis 2 (H2): higher process level would help to increase time-to-decision to FP&A decision making quality.

Hypothesis 3 (H3): having a higher data level would help to increase scenario and sensitivity analysis capability to FP&A decision making quality.

Hypothesis 4 (H4): higher organizational readiness level would help to increase actionability and strategic impact to FP&A decision making quality.

## 3. Method and Data

This article uses linear regression to explore the relationship between maturity and FP&A decision quality by quantifying both as scores from 0 to 5. The overall scores of independent and dependent variables are summed up from each score of the specific dimensions of independent and dependent variables. The scoring standard of the independent variables and dependent variables are shown in Table 1 and Table 2, respectively.

**Table 1.** Scoring Standard of Independent Variable

| Dimension / Standard | **Technology** | **Data** | **Process** | **Organizational Readiness** |
|---|---|---|---|---|
| 1 | Maturity of technical infrastructure | Data quality | Standardization of business processes | Commitment to change |
| 2 | Integration capability | Standardization and consistency | AI integration into workflow | Collective efficiency |
| 3 | Scalability of deployment | Data preprocessing and annotation maturity | Process flexibility and adaptability | Resource availability |
| 4 | Technical performance reliability | Data accessibility | Process monitoring and feedback loop | Executive support and communication |
| 5 | User technical accessibility | Applicability of AI data (fairness, bias, ethics) | Cross departmental process collaboration | Training and skill development |

**Table 2.** Scoring Standard of Dependent Variable

| Dimension / Standard | **Forecast Accuracy and Frequency** | **Time to Decision** | **Scenario and Sensitivity Analysis Capability** | **Actionability and Strategic Impact** |
|---|---|---|---|---|
| 0 | • Error > 20%<br>• Annual updates<br>• Only static budgeting<br>• Do not track error indicators | • 2 weeks to decide<br>• Fully manual systems<br>• Static reports<br>• Siloed operations | • No scenario modeling<br>• Annual budgets only<br>• Zero risk simulation | • Only provides past performance reports<br>• Zero strategic involvement |
| 1 | • Error 15% ~ 20%<br>• Semi-annual updates<br>• Minimal variance analysis<br>• Mostly manual processes | • 8-14 days latency<br>• Spreadsheet-dependent<br>• Minimal automation | • Ad hoc Excel scenarios<br>• 1-2 financial drivers<br>• No automation | • Occasionally joins planning<br>• Primarily handles budgets/costs |
| 2 | • Error 10% ~ 14%<br>• Quarterly updates<br>• Basic actual vs. forecast checks<br>• Limited BI tool usage | • 5-7 days delay<br>• Basic BI adoption<br>• Data-action disconnect | • Quarterly planning<br>• Revenue/cost focus<br>• Internal drivers only | • Supports operational planning<br>• Tracks strategic KPIs passively |
| 3 | • Error 7% ~ 9%<br>• Monthly updates<br>• BI dashboards for variance tracking | • 3–4-day cycle<br>• Unified dashboards | • Monthly cross-functional models<br>• External factors included<br>• Macroeconomic variables | • Advice on investments/products<br>• Evaluates cost restructuring |

| | | | | |
|---|---|---|---|---|
| | • KPI alignment | • Semi-auto approvals | | |
| 4 | • Error 5%~ 6%<br>• Monthly/rolling forecasts<br>• AI assists forecasting<br>• Frequent revisions | • 1–2-day turnaround<br>• AI generated insights<br>• Cross-team collaboration | • BI-integrated modeling<br>• Auto-updated data<br>• Live driver adjustments | • Active strategy reviews<br>• Uses forward-looking models |
| 5 | • Error ＜5%<br>• Continuous rolling forecasts<br>• AI/ML optimizes predictions<br>• High responsiveness to changes | • Instant decisions<br>• Live data & alerts<br>• AI scenario simulation | • AI predictive simulation<br>• Historical + external data<br>• Proactive risk optimization | • AI predicts strategy/M&A<br>• Drives long-term transformation |

The linear regression will be performed for both overall score and each independent variable of AI maturity. The overall score of AI maturity ($Y_{AI}$) is calculated from the four independent variables: technology, process, data and organizational readiness. The following equation indicates the mathematical model used for this analysis

$$Y_{AI} = \alpha_1 \cdot x_1 + \alpha_2 \cdot x_2 + \alpha_3 \cdot x_3 + \alpha_4 \cdot x_4 \tag{1}$$

In this equation, $\alpha_1$ to $\alpha_4$ refer to the contribution of each score from the independent variables ($x_1$ to $x_4$). In this research, the contribution of each independent variable to the overall AI and BI maturity of the company is set to be equal as they are four crucial criteria of AI adoption.

For comparison, the overall score reflecting the decision quality of FP&A of a company ($Y_{Quali}$) is calculated as,

$$Y_{Quali} = \beta_1 \cdot y_1 + \beta_2 \cdot y_2 + \beta_3 \cdot y_3 + \beta_4 \cdot y_4 \tag{2}$$

where $\beta_1$ to $\beta_4$ refer to the contribution of each score. Similarly, the four dependent variables also contribute equally to the overall score.

By evaluating results from linear regression, the main hypothesis and four sub hypotheses can be tested.

For the data acquisition of this research, the rest of this section describes the detailed method of obtaining the scores of each target firm for the rating model proposed in the method section.

Tencent achieves AI/BI maturity of 20/20 and FP&A decision quality of 19/20. Technology (5/5) is anchored by its cloud data platform and SiriusBI, which integrates across finance, advertising, and cloud units with 97% SQL accuracy. Tencent leverages LLMs for SQL generation, data transformation, and multi-round user queries [15]. Data maturity (5/5) is ensured through structured data lakes, standardized schemas, and rigorous quality audits. Processes (5/5) are standardized with AI-embedded workflows and continuous monitoring, while organizational readiness (5/5) is underpinned by RMB 70 billion annual AI investment, AI Lab and YouTu Lab, and extensive training programs. FP&A outcomes are equally strong: forecast accuracy and frequency (5/5), time to decision (5/5), scenario analysis (4/5), and strategic impact (5/5).

Lenovo records AI/BI maturity of 15.5/20 and FP&A decision quality of 15/20. Technology (5/5) is strong, leveraging ThinkSystem, ThinkEdge, and LUCI dashboards, while data maturity (3.5/5) is limited by incomplete bias audits despite 95% reporting efficiency. Processes (4/5) show wide deployment of AI-integrated workflows, though full automation is still evolving. Organizational readiness (3/5) reflects solid but uneven commitment, with 12,000 engineers trained and AI labs established, but training coverage remains partial. FP&A performance is mixed: forecast accuracy (4/5) from supply chain analytics, time to decision (5/5) via APS, but scenario analysis (3/5) and strategic impact (3/5) remain constrained, with reliance on Excel, BI dashboards, and quarterly review cycles.

Dah Sing Bank demonstrates AI/BI maturity of only 0.5/20 and FP&A decision quality of 6/20. Technology (0–1/5) is limited to conventional banking systems, with no evidence of proprietary BI or AI platforms. Data maturity (0/5) and process maturity (0/5) remain absent, with no standardized pipelines or embedded AI workflows. Organizational readiness (0/5) is also lacking, as disclosures show no governance, training, or strategic AI adoption. FP&A is weak: forecast accuracy (1/5) with 15–20% error rates, time to decision (2/5) at 5–7 days, scenario analysis (0.5/5) relying on manual modeling, and strategic impact (2/5) confined to compliance and operational monitoring.

# 4. Result

## 4.1. Test oft he Main Hypothesis

By performing the above calculation and plotting $Y_{Quali}$ against $Y_{AI}$, Fig. 1 is obtained.

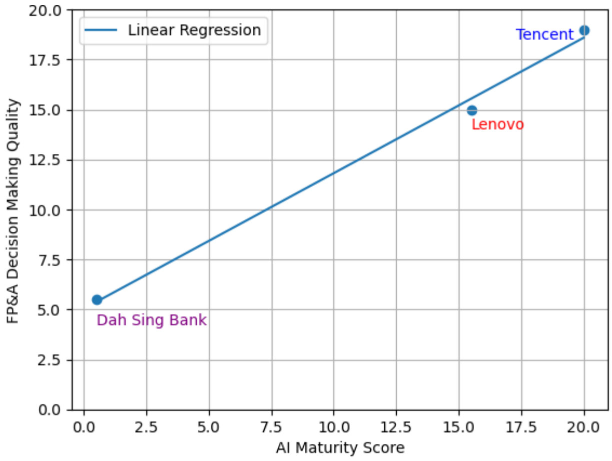


**Fig 1.** Correlation Diagram of FP&A Decision Making Quality vs. AI Maturity Score

Fig. 1 displays the correlation between AI maturity and the FP&A decision making quality of a company. According to the diagram, the company with higher AI maturity would have a higher FP&A decision making quality. This directly proves the main hypothesis. Because of higher AI maturity, reducing errors, less time to make decisions, more predictive simulation and more strategic involvement would improve decision making quality.

## 4.2. Test oft he Sub Hypothesis

To prove the sub hypothesis corresponding to each variable, aspect-specific analysis is also performed. For H1 which discussed correlation between technology and forecasting accuracy, Fig. 2 is obtained.

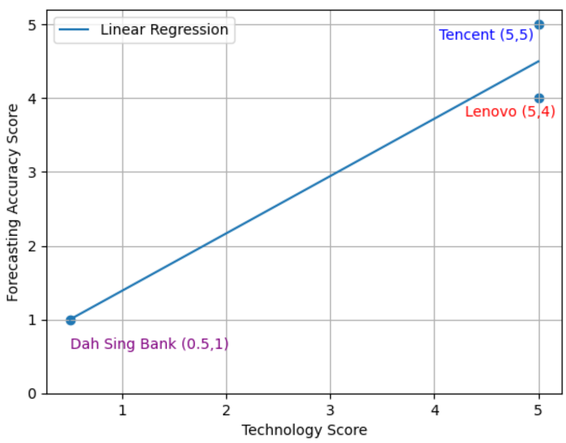


**Fig 2.** Correlation Diagram of Technology Level vs. Forecasting Accuracy Level

According to Fig. 2, Tencent and Lenovo have the same process score, 5, and Dah Sing Bank have the score 0.5. The case in which Tencent and Lenovo have the same technology score, but different time-to-decision scores are accidental. It is believed that having more companies investigated will show a more direct trend. From the linear regression line shown on the diagram, there is a positive correlation between these two variables, meaning that with the help of advanced technology, the forecasting accuracy can be increased. For example, advanced technology enables real-time data processing, scenario analysis, and forecasting. In addition, modern platforms, such as SAP Analytics Cloud, support predictive modeling and simulations in FP&A. Conversely, firms without up-to-date technology are more likely stuck in manual, descriptive reporting such as Excel-based reports due to incomprehensiveness in data and limited capability of handling complex data structures. For H2, which discussed process and time-to-decision, Fig. 3 is obtained.

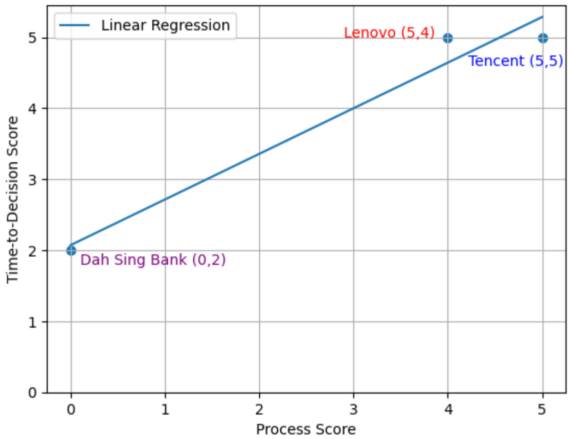


**Fig 3.** Correlation Diagram of Process Level vs. Time-to-Decision Level

According to Fig. 3, the positive correlation trend is clear according to the linear regression. Efficient predictive FP&A requires streamlined processes such as rolling forecasts and variance analysis. Therefore, having mature processes means having automated, efficient and real-time adaptive workflows. On the contrary, immature processes rely on backward-looking reporting cycles, leading to slow decision-making. For H3, which discussed data and scenario and sensitivity, Fig. 4 is obtained.

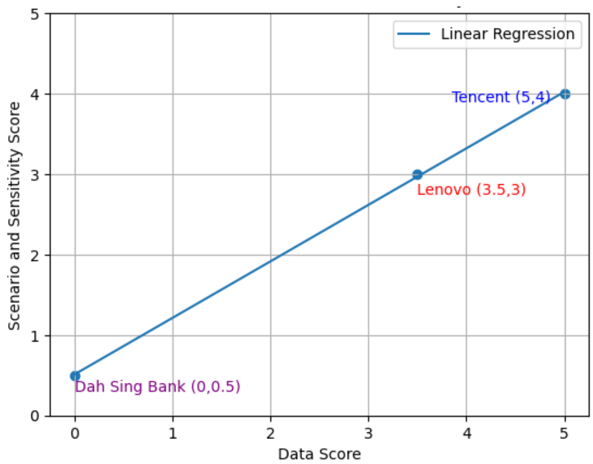


**Fig 4.** Correlation Diagram of Data Level vs. Scenario and Sensitivity Level

According to Fig. 4, the positive correlation between data and scenario and sensitivity score proves H3. With better data comprehension and accuracy, which eliminates data silos, forecasting models will be improved and manual adjustments are reduced, the analysis of AI and BI system can perform better analysis and a more realistic scenario simulation. In addition, integrated data allows holistic and forward-looking financial planning; companies with advanced AI maturity can model future uncertainty, simulate risk, and advise strategic decisions, for example cash flow risk simulations based on operational triggers. However, having a poor integration of data leads to inconsistent and less reliable reporting. For H4, which discussed organizational readiness and actionability and strategic impact, Fig. 5 obtained is shown below.

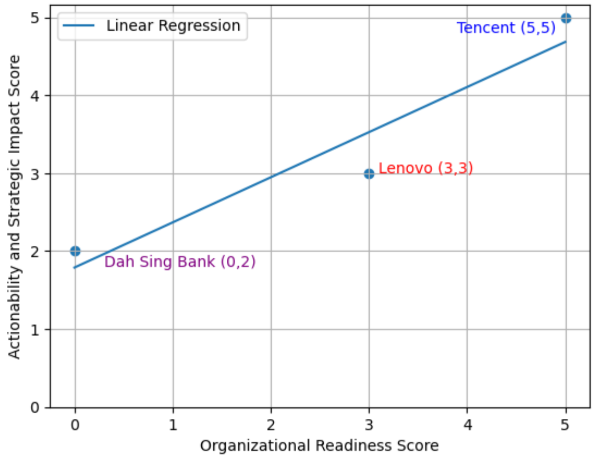


**Fig 5.** Correlation Diagram of Organizational Readiness Level vs. Strategic Impact Level

According to the diagram, the positive correlation between the organizational readiness score and actionability and strategic impact score proves H4. Even with good AI and BI tools, organizations with low readiness fail to elevate FP&A from support function to strategic advisor due to resistance, lack of skills, or siloed culture. Therefore, high readiness supports Human-AI collaboration and continuous learning, which is essential for interpreting AI-generated insights. The ultimate test of FP&A quality is whether it informs real strategic decisions.

## 5. Conclusion

This study builds a theoretical framework and empirically examines it to demonstrate FP&A decision effectiveness is closely linked with AI/BI maturity. High-maturity corporations such as Tencent achieve best-in-class FP&A performance in prediction accuracy, speed of decision, scenario planning, and strategic engagement while low-maturity corporations such as Dah Sing Bank remain beset with labor-intensive FP&A processes and disconnected data systems. At the technological level, real-time processing of data and advanced AI models—that represented by Tencent’s SiriusBI—are the foundation of predictive accuracy.

It shows insights into how firms can better incorporate AI and BI systems into their FP&A decision making process. Processes and automated workflows, such as Lenovo’s supply chain intelligence platform, can shorten decision-making cycles. A unified data platform and high-quality annotations, illustrated by Tencent’s Data Lake, can support complex analysis. High-level support and skill training, as seen in Lenovo’s AI laboratory, can ensure strategic implementation. Finally, enterprises can raise AI/BI maturity through systematic transformation rather than local optimization, with traditional financial institutions modernizing via cloud-native technology and cross-departmental collaboration.

There is potential for future research to generalize this study across other sectors such as healthcare, manufacturing, retailing, and government administration, where FP&A also plays a key role. Comparisons across industries would determine the framework's generalizability and determine sectoral challenges surrounding BI and AI adoption. Moreover, taking FP&A and AI ethics and bias in data into consideration would be valuable because issues of transparency, accountability, and fairness are increasingly affecting financial decision-making. Biases in training data or model bias might induce misleading forecasts and erode trust, and therefore FP&A systems must not only be efficient but also ethically resilient.

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