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Adoption of Data Analysis Tools in Financial Institutions: Factors Influencing Effectiveness

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ABSTRACT: This study investigates how organizational data literacy and technology infrastructure readiness affect the efficacy of data analysis tool adoption in financial organizations. It also looks into how top management support influences the relationship between technology infrastructure readiness and adoption effectiveness. A quantitative technique was used to collect data from 385 respondents—including bank staff, IT professionals, executives, and finance-sector policymakers—via structured interviews and online questionnaires. All responses were scored on a 5-point Likert scale, and participants were chosen through stratified probability sampling to guarantee representation across professional roles. Cronbach's alpha was used to assess reliability and validity, as well as exploratory factor analysis and multiple linear regression with moderation. The results show that both organizational data literacy and technology infrastructure preparation greatly improve adoption effectiveness. Notably, top management support enhances the favorable impact of technological infrastructure readiness on adoption outcomes, emphasizing the importance of leadership involvement in optimizing the value of analytics investments. This study adds to the literature by combining the Technology-Organization-Environment (TOE) paradigm with the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a socio-technical viewpoint on analytics adoption. Practical implications underscore the necessity for financial institutions to link technology assets with human talents and strategic leadership in order to maximize data-driven change.

KEYWORDS: Data Analysis Tool Adoption; Organizational Data Literacy; Technology Infrastructure Readiness; Top Management Support; Financial Institutions.

1. INTRODUCTION

The effectiveness of Data Analysis Tools Adoption in Financial Institutions has developed as an important study topic, indicating the industry's growing reliance on data-driven decision-making. While financial institutions invest extensively in advanced analytical tools, their actual efficiency is frequently limited due to organizational, technical, and cultural limitations (Davenport and Harris, 2007). Data silos, inadequate user training, and reluctance to change are common challenges that hinder intended outcomes (LaValle et al., 2011). Furthermore, assessing effectiveness is intrinsically hard because it includes both physical outcomes like operational efficiency and intangible benefits like better risk management and consumer insights (Marr, 2015). These considerations underscore the necessity for an empirical study to determine the fundamental drivers and contextual elements that influence adoption outcomes. Addressing this gap would not only assist in optimizing technological investments but would also improve financial institutions' competitiveness in an increasingly data-driven business.

Prior research on data analysis tool adoption in financial institutions has highlighted their revolutionary potential for improving decision-making, risk assessment, and customer engagement (Davenport & Harris, 2007; LaValle et al., 2011). Recent research has expanded on this by investigating organizational characteristics such as data culture and leadership support (Gupta et al., 2020). However, much of the research remains fragmented, with many studies focusing on either the technological or human elements without considering their interplay (Janssen et al., 2017). Furthermore, previous research tends to focus on major multinational banks, ignoring smaller institutions and regional contexts (Maroufkhani et al., 2020). This paper fills these gaps by combining organizational and technology drivers and investigating how top management support modifies their impact on adoption

effectiveness. This provides a more comprehensive understanding and practical recommendations for a wide range of financial institutions.
To improve theoretical understanding of this problem, the study will address these research questions:
1. How does organizational data literacy influence the efficacy of data analysis tool adoption in financial institutions?
2. What role does technological infrastructure readiness play in the success of data analytics tool adoption in financial institutions?
3. What steps does top management take to mitigate the impact of technology infrastructure readiness on the success of data analysis tool adoption in financial institutions?

Following these research topics, this study aims to investigate the direct effects of organizational data literacy and technology infrastructure preparedness on the success of data analysis tool adoption in financial institutions. Furthermore, the paper seeks to assess the extent to which top management support boosts or reduces the impact of technology preparedness on adoption results. Finally, the goal is to provide theoretical contributions to the academic discipline while also providing strategic advice for practitioners and financial executives to improve the deployment and use of data analytics tools in financial institutions.

2. LITERATURE REVIEW

2.1. Effectiveness of Data Analysis Tools Adoption in Financial Institutions

Effectiveness of Data Analysis Tools Adoption in Financial Institutions refers to the degree to which adopted analytical solutions improve decision-making, operational efficiency, and predictive accuracy in financial services (Maroufkhani et al., 2020). It is critical in helping institutions to convert raw data into strategic value by facilitating real-time risk assessment, fraud detection, and consumer behavior modeling (Rahma & Rahma, 2023). As financial institutions' operations become more complicated, effectiveness is defined not just by adoption but also by integration into processes and alignment with corporate skills. For example, JPMorgan Chase saved about 360,000 hours per year by effectively utilizing their COiN technology, which automates document analysis (Deloitte, 2020).

The effectiveness of data analysis tool adoption has become a strategic differentiator in financial institutions, with a greater emphasis on integration depth, interpretability, and operational alignment. While basic adoption is ubiquitous, efficacy varies due to differences in infrastructure readiness and user knowledge (Maroufkhani et al., 2020). Institutions with high data maturity show enhanced fraud protection, regulatory compliance, and client personalization, whereas others struggle due to siloed data cultures or a lack of managerial commitment (Rahma & Rahma, 2023). This variable is a proxy for an institution's analytical agility and innovation capability, making it critical to digital transformation success. Critically, quantifying efficacy requires both technical performance and behavioral uptake, emphasizing the socio-technical dimension of digital tool adoption in financial services.

2.2. Anchoring the theoretical framework

2.2.1. Technology–Organization–Environment (TOE) Framework Assumptions

According to the TOE paradigm, three contextual domains—technological, organizational, and environmental—influence an organization's decision to acquire and deploy technological innovations (Tornatzky & Fleischer, 1990; Awa et al., 2017). It is assumed that adoption efficacy is determined by the interaction of internal capabilities (e.g., infrastructure preparation, human capital) and external stimuli (e.g., competition, regulatory environments). Firms assess the relative advantage, complexity, and compatibility of a new technology while aligning internal processes and leadership support structures (Maroufkhani et al., 2020). The approach emphasizes that successful technology integration is not solely technical or administrative, but rather the consequence of a systematic interplay between both domains.

TOE gives an integrated perspective that is extremely significant to analyzing the effectiveness of data analysis tool adoption in financial institutions. Within this concept, Technology Infrastructure Readiness (TIR) denotes the firm's technological area, while Organizational Data Literacy (ODL) encompasses the organizational domain. TOE assumes that adoption success is determined by how successfully these domains co-evolve, particularly when combined with enabling environmental elements such as Top Management Support (TMS) (Awa et al., 2017). This theoretical lens is supported by actual findings that show that even well-developed IT systems fail to deliver value when end users lack the analytical skills to comprehend outcomes (Maroufkhani et al., 2020). TIR without ODL results in poor use, highlighting the importance of data-driven human capital. TMS also plays an important moderating role in TOE, serving as a managerial facilitator by aligning technical systems with corporate culture and practices. Studies have shown that senior management may reduce complexity obstacles, mobilize essential financial resources, and institutionalize data-driven decision-making procedures (Ifinedo, 2011). Thus, TMS serves as a link between technology preparedness and adoption effectiveness, especially important in hierarchical institutions such as banks, where change programs frequently fail owing to a lack of leadership support. In the case of financial institutions, the TOE paradigm indicates that infrastructure alone is insufficient; organizational readiness—both cultural and cognitive—is also critical (Tajudeen et al., 2018).

In conclusion, the TOE model supports the multi-layered interaction of TIR, ODL, and TMS and shows how their synergy might maximize data analytics adoption. It moves beyond restricted technical perspectives by incorporating management and structural enablers into the technology adoption process.

2.2.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

According to the Unified Theory of Acceptance and Use of Technology (UTAUT), performance expectancy, effort expectancy, social influence, and facilitating factors all have a significant impact on user adoption and usage behavior. It is assumed that these parameters are moderated by experience, voluntariness, and organizational support (Venkatesh et al., 2012). UTAUT also assumes that behavioral intention precedes actual use, with perceived simplicity and benefit of technology directly influencing efficacy. It is assumed that leadership endorsement and supported infrastructure increase user engagement with technologies, particularly in institutional settings.

UTAUT adds a behavioral and cognitive lens to organizational models like TOE by concentrating on individual-level mechanisms of technology use. In this study, Organizational Data Literacy directly correlates with effort expectancy, which indicates the perceived ease of utilizing data tools due to prior knowledge or training (Venkatesh et al., 2003). Financial institutions with higher levels of ODL are more likely to have successful implementations because employees see data tools as accessible and helpful, boosting usage frequency and competency (Rahman & Rahman, 2023). Furthermore, Technology Infrastructure Readiness coincides with facilitating conditions, measuring how users perceive helpful technology surroundings. Top Management Support has a similar role to social influence in UTAUT, in which senior executives' behavior and endorsement effect staff attitudes and behaviors. Employees are more likely to understand the value of data tools when leadership not only requires their use, but also models and promotes data-driven decisions (Venkatesh et al. 2012). This relationship is especially important in highly regulated and risk-averse environments like banks, where managerial support has normative and strategic implications. Prior research confirms that great leadership may overcome institutional inertia and create supportive environments for innovation (Dwivedi et al., 2019). Furthermore, UTAUT's high explanatory power (accounting for around 70% of the variance in behavioral intention) makes it an effective paradigm for understanding why some organizations fail to reap the benefits of adoption while having the necessary tools and infrastructure in place. The success of adoption, as the dependent variable, is presented here not only as the output of technology use, but also as a result of aligned human attitudes, motivations, and environmental scaffolding—exactly what UTAUT was intended to simulate.

Thus, incorporating UTAUT into this study allows for a more nuanced understanding of how internal preparation (data literacy), structural factors (infrastructure), and hierarchical effects (top management) combine to yield effective adoption outcomes. The approach underscores the idea that adoption effectiveness is a socio-technical process that necessitates not only technological investment but also human preparedness and strategy alignment.

2.3. Determinants of Effectiveness of Data Analysis Tools Adoption in Financial Institutions

2.3.1. Organizational Data Literacy

Organizational Data Literacy refers to a firm's collective ability to read, analyze, communicate, and utilize data in decision-making processes at all levels (Mandinach & Gummer, 2016). It extends beyond technical proficiency to include the cultural, strategic, and behavioral competencies required to convert raw data into actionable insights (Deja et al., 2021). Theoretically, it is consistent with the firm's resource-based view (RBV), which views intangible resources such as data competency as a source of long-term competitive advantage (Barney, 1991). As data becomes more important in operations, Organizational Data Literacy enables organizations to not only gather and process information, but also to integrate analytics into strategic functions. According to some studies, organizations with stronger data literacy outperform their peers in terms of innovation, customer experience, and agility. Despite its expanding importance, many businesses struggle to institutionalize data literacy, especially in hierarchical or compliance-heavy industries such as finance, where analytical thinking is frequently limited to technical departments (Aziz, 2023).

The amount of organizational data literacy has a significant impact on the extent to which data analysis technologies provide concrete benefits in financial organizations. High data literacy improves interpretative accuracy, develops data-driven cultures, and minimizes resistance to analytical integration—all of which are necessary for effective tool adoption. According to Rahman & Rahman (2023), data-literate personnel are more likely to use analytical platforms, trust algorithmic outputs, and incorporate insights into processes, increasing the return on data infrastructure investments. Firms that lack data literacy, on the other hand, risk "technology in name only" scenarios in which capabilities are underutilized or misapplied, resulting in data silos rather than strategic insight (Maroufkhani et al., 2020).

Several empirical studies support a direct positive association between organizational data literacy and adoption outcomes. For example, Gupta and George (2016) discovered that businesses with data-literate cultures not only implemented analytics more successfully but also integrated them into strategic operations, resulting in significant performance increases. Similarly, Wang et al. (2019) found that data-savvy firms have higher predictive capacities and more agile responses to market movements, which is especially important in the dynamic financial services environment. However, the strength and constancy of this link are debatable. Some studies suggest that, while data literacy improves tool efficacy, its impact is mediated by other organizational characteristics such as managerial support, change preparedness, or even the sector's regulatory framework. For example, Akter et al. (2016) present a moderated view in which literacy must be combined with leadership commitment and cultural readiness in order to create measurable results. Even in extremely bureaucratic or compartmentalized businesses, high levels of individual data literacy may not convert into corporate effectiveness unless backed by institutional support and shared vision.

Data literacy is philosophically aligned with pragmatism, which emphasizes the utility of information through action and consequences. In Dewey's tradition, knowledge is not an end in itself, but rather a means to an end, similar to how data literacy leads to more grounded and effective decision-making in dynamic situations (Dewey, 1938). Economically, this is consistent with information asymmetry theory (Akerlof, 1970), which states that data literacy can reduce internal inefficiencies by allowing transparent, evidence-based decisions across hierarchical tiers, hence improving operational equilibrium.

In combining these ideas, the authors argue that organizational data literacy is a strategic facilitator rather than a peripheral talent. It serves as an interpretive bridge between complex technologies and relevant applications. Its existence decides whether financial organizations can migrate from passive data possession to active data utilization, resulting in measurable improvements in speed, compliance, and customer satisfaction.

H1: Organizational Data Literacy positively impacts the Effectiveness of Data Analysis Tools Adoption in Financial Institutions.

2.3.2. Technology Infrastructure Readiness

Technology Infrastructure Readiness (TIR) is the extent to which an organization has technology systems in place, including hardware, software, networks, cloud computing, and security, to support digital transformation activities, including the application of data analytics tools (Bharadwaj, 2000). According to the TOE (Technology–Organization–Environment) framework, technology infrastructure is a fundamental factor that supports the ability to absorb innovation (Tornatzky & Fleischer, 1990). TIR is a critical enabler of digital transformation in financial institutions, allowing for the seamless installation of data analysis technologies such as business intelligence systems, machine learning algorithms, and AI-powered analytics platforms. It not only represents the organization's capability to deploy such technologies but also its resilience to technological failures, scalability, and real-time performance (Hussain & Papastathopoulos, 2022). According to the resource-based view (RBV), technology infrastructure is a strategic resource that can provide a long-term competitive advantage if it is valuable, rare, unique, and well-organized (Barney, 1991; Bharadwaj, 2000). Even highly advanced data analytics technologies may fail to offer a meaningful impact if the technical infrastructure is not adequately prepared due to implementation gaps or system incompatibilities.

TIR remains uneven between organizations. While companies in industrialized countries invest extensively in scalable cloud systems and data pipelines, many in emerging economies struggle with obsolete infrastructure and poor integration (Liao et al., 2024). TIR is both technical and strategic; without alignment between IT capability and corporate goals, the adoption of data analytics tools may stall (Bharadwaj, 2000). Financial firms with strong TIR are more agile, compliant, and innovative, whereas those with fragmented systems face increased operational risks (Sarathy, 2023).

From a phenomenological perspective, technology is a “means for action” and only truly makes sense when it is “ready-to-hand” in a specific action context (Heidegger, 1962). When TIR is in good shape, it integrates into the work ecosystem, allowing the organization to focus on strategic goals such as data analysis, rather than constantly troubleshooting technical problems. From an endogenous growth economics perspective, investment in technological infrastructure is a form of capital that boosts total factor productivity (TFP), a core element in endogenous growth theory. Improving TIR helps financial institutions process big data, make quick decisions, and optimize operations, thereby enhancing competitive advantage (Parasuraman & Colby, 2015).

When TIR is established and managed effectively, it provides a stable foundation for data systems, including technologies such as cloud, data lakes, and AI-ready stacks, helping financial institutions fully exploit the potential of data analytics, thereby significantly and sustainably enhancing the effectiveness of analytics adoption (Sarathy, 2023; Najem et al., 2025). Previous studie give two opposing arguments about the impact of TIR on the effectiveness of data analysis tool adoption in financial institutions. A study of 297 banks in China found that the development of big data infrastructure at the national level has driven FinTech innovation, especially in large banks with low credit risk ($\beta>0$) (Muganyi et al., 2022; Liao et al., 2024). A report from Informs/Analytics Magazine found that more than 60% of CIOs at financial institutions plan to invest heavily in infrastructure, such as security, APIs, and cloud, to support BI & data analytics as a foundation for growth and compliance (Sarathy, 2023). However, there is evidence that infrastructure alone, without supporting elements such as data awareness, training, or senior leadership strategy, TIR only plays a neutral role. For example, storing dark data, if not handled well, can reduce the reliability and quality of analytics (Techradar, 2025). The FT report warns that financial institutions that rely on complex technology without investing in adequate security, testing, and systems governance will face serious risks—such as service outages or system failures—even with modern infrastructure (FT, 2025).

Thus, having a ready technology infrastructure is proven to be a necessary condition for financial institutions to increase the efficiency of deploying data analytics tools; however, to achieve strong, sustainable impact, it needs to be combined with a data governance strategy, training and support from senior leadership.

H2: Technology Infrastructure Readiness positively impacts Effectiveness of Data Analysis Tools Adoption in Financial Institutions.

2.3.3. Moderating Role of Top Management Support

Top Management Support (TMS) refers to the degree to which senior leadership actively promotes, facilitates, and allocates resources to a given technology or strategic project (Al-Omoush, 2021). TMS is critical in determining whether organizational innovation efforts succeed or fail, especially in complex environments like financial institutions. The Resource-Based View (RBV) approach stresses management competencies and organizational support as strategic resources that influence technical competitiveness and company success (Barney, 1991). According to institutional theory, TMS helps to legitimize the deployment of new technologies, particularly in highly regulated areas (Scott, 2013). TMS ensures that digital transformation efforts are aligned with business goals by facilitating funding, overcoming resistance, and establishing accountability frameworks (Sabir et al., 2023). The absence of TMS frequently results in resource fragmentation, lack of commitment, and inadequate analytics platform adoption (Shao, 2019).

While digital transformation has gained traction, empirical research reveals that TMS is frequently mismatched with bottom-up innovation initiatives. For example, in financial services, just 46% of analytics installations are supported by strategic leadership vision, with the majority driven by middle management or IT divisions (Kiron et al., 2014). This misalignment leads to finance, training, and cross-departmental integration gaps, all of which are critical components of efficient data tool adoption. Furthermore, many C-suite executives lack digital expertise, making them hesitant to prioritize long-term infrastructure development (Aldboush & Ferdous, 2023). Such strategic myopia prevents the widespread use of analytics tools, resulting in short-term experimental experiments rather than scalable success.

From a critical management perspective, TMS is not only instrumental but also symbolic—its visibility reinforces a transformational culture. According to Michel Foucault's power-knowledge theory, leadership support serves as a tool for institutionalizing new forms of knowledge, such as analytics, via hierarchical influence and organizational discourse. From a neoclassical economics perspective, management assistance can be viewed as an input element that increases company productivity. TMS reallocates firm-level capital, such as budget and attention, to information-based decision-making, boosting the marginal return on infrastructure readiness investments (Penrose, 2009; Teece, 1986).

While Technology Infrastructure Readiness (TIR) is an important predictor of analytics adoption, it does not ensure effective utilization. TMS's moderating influence is critical in translating technical capabilities into functional outcomes (Xu et al., 2024). TMS closes the gap between "technological potential" and "strategic realization" by fostering organizational commitment, prioritizing cross-departmental cooperation, and encouraging risk-taking in data initiatives. When TMS is high, TIR translates more effectively into greater use, confidence, and ROI of data products. However, in the absence of TMS, strong infrastructure may be underutilized due to a lack of direction, fragmented governance, or cultural opposition (Shao, 2019; Sabir et al., 2023).

The literature has two contrasting arguments about the nature of TMS's moderation. Some scientists think that TMS enhances TIR's favorable effect on EDATA. Organizations with high TMS fully utilize infrastructure capabilities, resulting in improved analytics performance (Al-Omoush, 2021; Sabir et al., 2023). Others argue that TMS could operate as a neutralizer, reducing heterogeneity in outcomes by standardizing organizational responses independent of TIR. That is, with powerful TMS, even modest infrastructure can produce good results thanks to effective top-down coordination and adaptive techniques (Xu et al., 2024). This duality parallels broader discussions in contingency theory, in which the influence of a contextual variable, such as TMS, is determined not just by its presence but also by how it interacts with underlying technological and cultural contexts.

H3: Top Management Support moderates the relationship between Technology Infrastructure Readiness and the Effectiveness of Data Analysis Tools Adoption in Financial Institutions, such that the relationship is stronger when Top Management Support is high.

With the hypotheses firmly entrenched in a solid theoretical foundation, this study expands its scholarly usefulness by proposing the following conceptual framework.

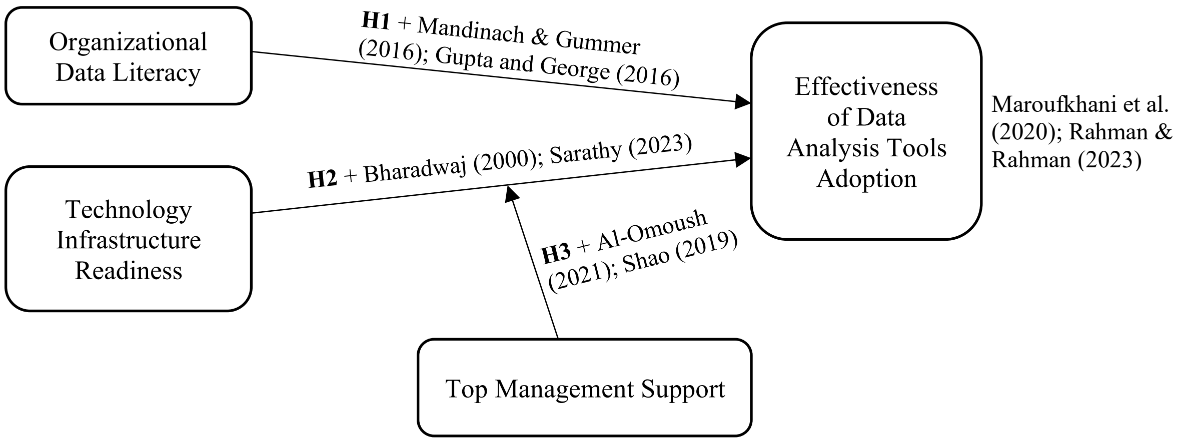

Figure 1. The paper's conceptual framework (Authors, 2025)

3. METHODOLOGY

This study adopts a quantitative methodology, allowing for systematic data collecting and analysis to find and validate underlying links between organizational, technological, and managerial characteristics in financial institutions (Creswell & Creswell, 2017). Quantitative research enhances objectivity and precision by employing statistical procedures to investigate causal relationships and moderating effects between constructs, such as Organizational Data Literacy, Technology Infrastructure Readiness, and Top Management Support (Babbie, 2020).

To ensure validity and contextual relevance to the Vietnamese financial sector, the study used a stratified probability sampling method. This method ensured representativeness among four key stakeholder groups that are heavily involved in data-driven decision-making and analytics adoption. The first category included bank employees and mid-level managers (34%), who worked directly with analytics tools in operational procedures such as credit risk assessment, fraud detection, and customer segmentation. The second group included IT and digital transformation specialists from financial institutions (27%), who provided insights into infrastructure readiness and technology integration. A third group (22%) included executive-level decision-makers (such as CFOs, CIOs, and department heads), whose top-down support was critical in enabling analytics-driven strategies and aligning data initiatives with organizational priorities. The final group (17%) consisted of academic researchers, consultants, and policymakers from the finance sector, whose opinions helped contextualize business developments and regulatory implications.

Primary data were gathered through both structured face-to-face interviews and online self-administered surveys using Google Forms. The questionnaire was distributed through professional associations, internal banking networks, LinkedIn groups, and specialist financial discussion platforms in Vietnam, including "Phân tích dữ liệu & Tài chính số" and "Chuyển đổi số Ngân hàng Việt Nam." To assess respondent impressions of all measuring items developed from the literature study, the survey employed a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

After removing incomplete or inconsistent inputs, a final dataset of 385 valid responses was maintained from the 812 collected submissions. This cleaned dataset served as the empirical foundation for further statistical analyses, such as validity evaluation, regression modeling, and moderation testing.

4. RESULTS

4.1. Reliability analysis

Table 1: Reliability analysis of "smart grid operational efficiency". Source: (The authors, 2025)

Reliability Statistics

Cronbach's Alpha	N of Items
.754	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DATA1	6.919	7.009	.725	.736

DATA2	7.803	7.258	.704	.722
DATA3	7.306	7.987	.635	.639
DATA4	7.223	7.327	.599	.628

Where survey items DATA1–DATA4 were designed for 4 survey questions of the dependent variable respectively. As indicated in Table 1, each dependent sub-variable achieved an adjusted item–total correlation of at least 0.3. The overall Cronbach's alpha reached 0.754, surpassing the accepted minimum benchmark of 0.7 and proving higher than any alternative alpha that would have been obtained by deleting individual items. Moreover, all sub-items reported Cronbach's alpha values greater than their respective adjusted item–total correlations, even when examined independently. Consequently, all four items were considered reliable and retained for subsequent analysis. Comparable reliability patterns were also found in the Cronbach's alpha results of the other constructs.

4.2. Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix. Source: (The authors, 2025)

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
DATA1 .702 DATA2 .635 DATA3 .685 DATA4 .624	ODL1 .520 ODL2 .596 ODL3 .683 ODL4 .644	TIR1 .611 TIR2 .500 TIR3 .754 TIR4 .633	TMS1 .606 TMS2 .585 TMS3 .675 TMS4 .775
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Where te survey items ODL1–ODL4, TIR1–TIR4, and TMS1–TMS4 were designed to capture the two independent variables and the moderator, with four questions representing each construct.

As shown in Table 2, the rotated component matrix successfully categorized the 16 sub-items into four distinct factors that aligned precisely with the dependent variable, the two independent variables, and the moderator. All items demonstrated factor loadings exceeding the 0.5 benchmark, confirming their appropriateness for the constructs. Therefore, none of the items were eliminated during factor analysis, underscoring strong construct validity across all variables.

4.3. Multiple linear regression model

Table 3: Coefficients[a]. Source: (The authors, 2025)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	6.373	.774		4.008	.000
1	ODL	.632	.865	.690	3.995	.000
	TIR	.516	.785	.570	3.665	.000

a. Dependent Variable: DATA

Where **DATA**: mean of DATA1 to DATA4; **ODL**: mean of ODL1 to ODL4; **TIR**: mean of TIR1 to TIR4

As shown in Table 3, the t-test results produced significance (Sig.) values of .000, both of which are below the conventional alpha threshold of 0.05. This confirms that the independent variables exert a statistically significant effect on the dependent variable. Thus, the results offer empirical validation for both of the proposed hypotheses.

4.4. Moderator analysis

Table 4: Results analysis of "Effectiveness of Data Analysis Tools Adoption". Source: (The authors, 2025)

Model : 1
Y : DATA
X : TIR
W : TMS
Sample Size: 385

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OUTCOME VARIABLE:
DATA
Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.665	.442	.536	5.878	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	7.050	.675	61.881	.000	7.800	7.443
TIR	.623	.696	4.802	.000	.765	.747
TMS	.537	.699	4.360	.000	.885	.834
Int_1	.510	.836	4.561	.000	.676	.613

Where **TMS**: mean of TMS1 to TMS4

As reported in Table 4, the p-value for the interaction term (Int_1) is 0.000, which is far below the conventional significance threshold of 0.05. This indicates a statistically significant interaction effect between top management support and technology infrastructure readiness on the success of data analysis tool adoption in financial institutions. With an interaction coefficient of 0.510, the results suggest that higher levels of top management support enhance the positive impact of technology infrastructure readiness on the success of data analysis tool adoption in financial institutions. Therefore, hypothesis H3 is empirically validated.

5. DISCUSSION

5.1 Summary results

Organizational data literacy and technological infrastructure readiness contribute positively to the efficacy of data analysis tool adoption in financial institutions, with respective effect sizes of 0.69 and 0.57. Additionally, top management serves as a moderating factor, strengthening the relationship between technology infrastructure readiness and the success of data analysis tool adoption in financial institutions, with a moderation coefficient of 0.51.

5.2 Theoretical Implication

The high empirical evidence for H1 ($\beta = 0.69$) supports the hypothesis that organizational data literacy (ODL) is a foundational driver of successful data tool adoption, consistent with Gupta and George (2016) and Rahman & Rahman (2023). This study supports the concept that ODL develops a data-driven culture, which increases interpretative capacity and integration depth. However, it somewhat contradicts Akter et al. (2016), who argue that literacy alone is insufficient in the absence of cultural and administrative support. The study's findings contradict their viewpoint by proving that, even in moderately bureaucratic contexts, strong ODL can produce significant effectiveness benefits on its own. Furthermore, although Aziz (2023) and Mandinach & Gummer (2016) highlight literacy at the individual level, this study emphasizes its collective, strategic relevance as an organizational asset, which aligns with the RBV viewpoint (Barney, 1991). Thus, ODL emerges not just as technical expertise but also as institutional competence that serves as a direct link between tool availability and impactful utilization, particularly in high-stakes decision-making situations.

The findings for H2 ($\beta = 0.57$) confirm that Technology Infrastructure Readiness (TIR) is a substantial enabler of analytics adoption effectiveness, which supports Bharadwaj (2000) and Hussain & Papastathopoulos (2022). However, this analysis calls into question the deterministic idea that a strong infrastructure guarantees success. In contrast to Muganyi et al. (2022), who emphasize national-level infrastructure as the primary catalyst for FinTech innovation, our findings are more consistent with the cautionary stance of TechRadar (2025) and FT (2025), which warn against overreliance on "cold" infrastructure without "soft" supports such as data governance and training. While Sarathy (2023) describes TIR as foundational, this study contends that its impact is dependent on alignment with organizational context and user competence. This theoretically supports Heidegger's phenomenological perspective, as technology becomes significant only when it is "ready-to-hand." As a result, while the study largely agrees with TIR's priority, it rejects the concept that it is sufficient in isolation, instead calling for a balanced socio-technical integration. It calls on scholars to reconsider RBV's perspective of IT infrastructure as a strategic asset, taking into account its interaction with human readiness and institutional vision.

Top Management Support (TMS) has a positive moderation effect on the TIR-effectiveness link ($\beta = 0.51$), confirming its centrality as a strategic amplifier, as suggested by Al-Omoush (2021) and Sabir et al. (2023). The data confirm that TMS not only enables resources but also legitimizes analytics adoption through symbolic and structural mechanisms, reflecting Foucault's power-knowledge hypothesis. However, the data contradict Xu et al. (2024) in claiming that TMS neutralizes infrastructural diversity by equating organizational responses. Instead, our study shows that TMS strengthens rather than equalizes asymmetrical TIR advantages, especially when leadership is digitally literate and communicatively engaged. It also calls into question Kiron et al. (2014) in their claim that analytics success is frequently the result of middle-management initiative; in this case, strategic alignment emerged only when C-level engagement was strong. Thus, TMS is more than just a passive moderator; it is an active catalytic factor that shapes how infrastructure converts into value. This sophisticated understanding adds to contingency theory by demonstrating how management assistance affects infrastructure maturity levels and organizational preparedness circumstances.

5.3 Practical Implications

The findings of this study have far-reaching consequences for financial firms looking to improve the usefulness of data analysis tools. First, the strong impact of Organizational Data Literacy (ODL) on adoption outcomes implies that infrastructure investments should be accompanied by intentional human capital development. Institutions should not only provide technical training, but also develop a culture of data-driven decision-making at all levels of the organization. This entails incorporating data literacy into employee onboarding, leadership training, and performance measures, which is consistent with the study's assessment of ODL as a strategic asset rather than a supporting function.

Second, while Technology Infrastructure Readiness (TIR) improves tool efficacy, the study warns against viewing infrastructure in isolation. Institutions must go beyond basic hardware and software purchase to prioritize system integration, compatibility, and real-time analytics functionality. This involves investments in cloud-based platforms, secure APIs, and powerful data warehouses that are designed for regulatory compliance and operational agility. More importantly, IT teams must work with operational divisions to ensure that infrastructure development meets end-user requirements and business objectives.

Third, the moderating function of Top Management Support (TMS) shows that leadership buy-in is more than just a peripheral facilitator; it is a predictor of return on technology expenditures. Senior executives must not only allocate resources, but also publicly support data initiatives, set standards for evidence-based procedures, and actively model the use of analytics in strategic choices. Managerial advocacy, particularly in hierarchical institutions such as banks, has a symbolic and operational role in promoting organizational commitment and overcoming change opposition. The findings highlight how even well-prepared infrastructure might fail to deliver value if leadership does not institutionalize its importance.

Overall, the findings highlight the importance of a coordinated strategy that combines technical infrastructure, data fluency, and senior leadership. Financial institutions, particularly in emerging economies, should implement an integrated analytics readiness framework that matches technology assets with cognitive and cultural competencies in order to enhance data-driven transformation.

5.4 Limitations

This study, while well-designed, is limited in its geographic and institutional reach. The sample was only obtained from Vietnamese financial institutions, which may limit its applicability to other regulatory, technological, or cultural situations. Furthermore, the survey's cross-sectional design captures perceptions at a single time point, which limits causal inference. Although the study included a wide range of professional responsibilities, it may have underestimated the complexities of intra-organizational power dynamics or informal practices that influence adoption. Finally, relying on self-reported measurements may entail social desirability or response biases, especially in terms of top management support and organizational literacy.

5.5 Future Research Directions

Future research should use longitudinal designs to track the temporal evolution of data tool use and its organizational implications. A cross-country comparative study would also be useful, particularly when comparing mature and developing economies to highlight contextual dependencies in infrastructure and leadership efficacy. Incorporating qualitative methodologies such as interviews or ethnography may also help to better understand behavioral and cultural facilitators or resistances. Future research may also look into the influence of mid-level management or data governance bodies in influencing adoption outcomes, broadening the leadership lens beyond top management. Finally, investigating the integration of AI-driven analytics with traditional tools might improve our understanding of hybrid adoption models and their implications for workforce reskilling.

5.6 Conclusion

This study shows that the success of data analysis tool adoption in financial institutions is highly influenced by organizational data literacy and technology infrastructure readiness, with top management assisting in enhancing the infrastructure-effectiveness correlation. By combining the TOE and UTAUT frameworks, the study presents a holistic view of adoption dynamics, connecting the technical, cognitive, and strategic aspects of digital transformation. Practical implications emphasize the importance of coordinated investments in technology and human capital, directed by dedicated leadership. While contextual, the findings provide strategic insights for financial firms looking to turn analytical capability into tangible benefit. Future research should refine and broaden these insights to encompass broader institutional and geographic contexts.

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APPENDIX

Table 1. Survey Questionaire

Background information

1	What is your current role within the financial sector?	Banking operations staff	IT/Data analytics specialist	Executive/Top management (e.g., CFO, CIO)	Academic researcher / Consultant / Policy advisor	Other
2	How many years of experience do you have working in the financial services industry?	Less than 1 year	1–3 years	4–7 years	8–10 years	More than 10 years
3	What type of financial institution are you currently affiliated with?	Commercial bank	Investment bank or securities company	FinTech or digital financial services firm	Government agency or academic institution	Other
4	Have you had prior experience using data analysis tools (e.g., Power BI, Tableau, SAS, R, Python) in your work?	Yes, regularly	Occasionally	Rarely	Never	

No.	Variables	Coded Sub-variables	Content
1.	Effectiveness of Data Analysis Tools Adoption in Financial Institutions (Dependent variable)	DATA1	The adoption of data analysis tools in my institution has improved decision-making processes (Maroufkhani et al., 2020)
		DATA2	Data analysis tools have enhanced our ability to detect risks and prevent frauds (Rahman & Rahman, 2023)
		DATA3	The integration of analytics tools has improved customer insights and service quality (Rahman & Rahman, 2023)
		DATA4	Data analysis tools are effectively embedded into daily operational activities (Maroufkhani et al., 2020)
2.	Organizational Data Literacy (Independent variable 1)	ODL1	Employees in my institution have sufficient skills to interpret and analyze data effectively (Mandinach & Gummer, 2016)
		ODL2	There is a strong culture of data-driven decision-making across departments (Gupta & George, 2016)
		ODL3	Staff members are confident in utilizing data analysis tools to inform their tasks (Rahman & Rahman, 2023)
		ODL4	Training programs are regularly provided to improve data literacy among employees (Mandinach & Gummer, 2016)
3.	Technology Infrastructure Readiness (Independent variable 2)	TIR1	My institution has adequate IT infrastructure (e.g., cloud, servers, security) to support data analytics tools (Bharadwaj, 2000)
		TIR2	The current systems and software in use are compatible with advanced analytics tools (Sarathy, 2023)
		TIR3	Our data infrastructure allows for fast, real-time analytics performance (Hussain & Papastathopoulos, 2022)
		TIR4	Technical issues rarely hinder the functioning of our data analytics systems (Sarathy, 2023)
4.	Top Management Support (Moderator)	TMS1	Senior management actively supports the use of data analytics tools in the organization (Al-Omoush, 2021)
		TMS2	Top executives allocate sufficient resources for the adoption and maintenance of analytics systems (Sabir et al., 2023)
		TMS3	Management consistently communicates a clear vision for data-driven transformation (Shao, 2019)
		TMS4	Leadership involvement motivates staff to engage with and utilize data analytics tools (Sabir et al., 2023)

Survey link: https://forms.gle/bJ8EcnLEb6oxbzjV8