



The Impact of Interactive Dashboard Visualization on Data-Driven Decision Making in Financial Services: A Qualitative Evaluation

Sadia Zaman¹; Maishar Mostari Zenia²;

[1]. Business Analyst, Dhaka, Bangladesh;
Email: zaman.sadia1311@gmail.com

[2]. Web Development Intern, Kodeeo Limited, Dhaka, Bangladesh;
Email: zenia@kodeeo.com

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Abstract

This study examines the problem that financial-service organizations increasingly invest in interactive dashboards and business intelligence systems, yet the availability of sophisticated visualization technology does not necessarily ensure accurate, timely, evidence-based, and analytically informed decision making. The purpose of the research is to quantitatively assess how specific interactive dashboard visualization capabilities influence Data-Driven Decision-Making Performance in financial-service organizations and to determine their individual and combined predictive contributions. Although the paper title refers to a qualitative evaluation, the implemented methodology is explicitly quantitative, cross-sectional, and case-study-based, focusing on selected enterprise financial-service cases, including banks, insurance companies, investment firms, lending institutions, and fintech organizations using interactive dashboards for operational, risk-related, analytical, and managerial decisions. A purposive sample of financial managers, business and data analysts, risk and credit professionals, operations and compliance personnel, and BI, IT, and analytics specialists was surveyed using a five-point Likert-scale instrument. Of 320 questionnaires distributed, 298 were returned and 284 usable responses were retained, producing an 88.8% usable response rate. The key independent variables were Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability, while Data-Driven Decision-Making Performance served as the dependent variable. Data analysis incorporated descriptive statistics, Cronbach's alpha, Pearson correlation, multiple regression, ANOVA, standardized beta coefficients, R^2 , adjusted R^2 , VIF, tolerance, and Durbin-Watson diagnostics. The findings showed that Data-Driven Decision-Making Performance achieved $M = 4.21$, $SD = 0.52$, while Visual Information Quality Recorded $M = 4.18$, $SD = 0.54$. All predictors were positively and significantly associated with decision performance, with Visual Information Quality showing the strongest correlation, $r = .72$, $p < .001$, followed by Real-Time Analytical Capability, $r = .70$, Dashboard Interactivity, $r = .68$, and Dashboard Usability and Accessibility, $r = .61$. The regression model produced $R = .834$, $R^2 = .696$, adjusted $R^2 = .692$, $F(4, 279) = 159.69$, $p < .001$, explaining 69.6% of the variance. Visual Information Quality was the strongest predictor, $\beta = .30$, followed by Real-Time Analytical Capability, $\beta = .28$, Dashboard Interactivity, $\beta = .24$, and Dashboard Usability and Accessibility, $\beta = .17$. All five hypotheses were supported. These results imply that financial enterprises should prioritize high-quality visual information, timely analytics, meaningful interactivity, and accessible dashboard design to strengthen evidence-based financial decision performance.

Keywords

Interactive Dashboard Visualization; Data-Driven Decision Making; Visual Information Quality; Real-Time Analytics; Financial Services;

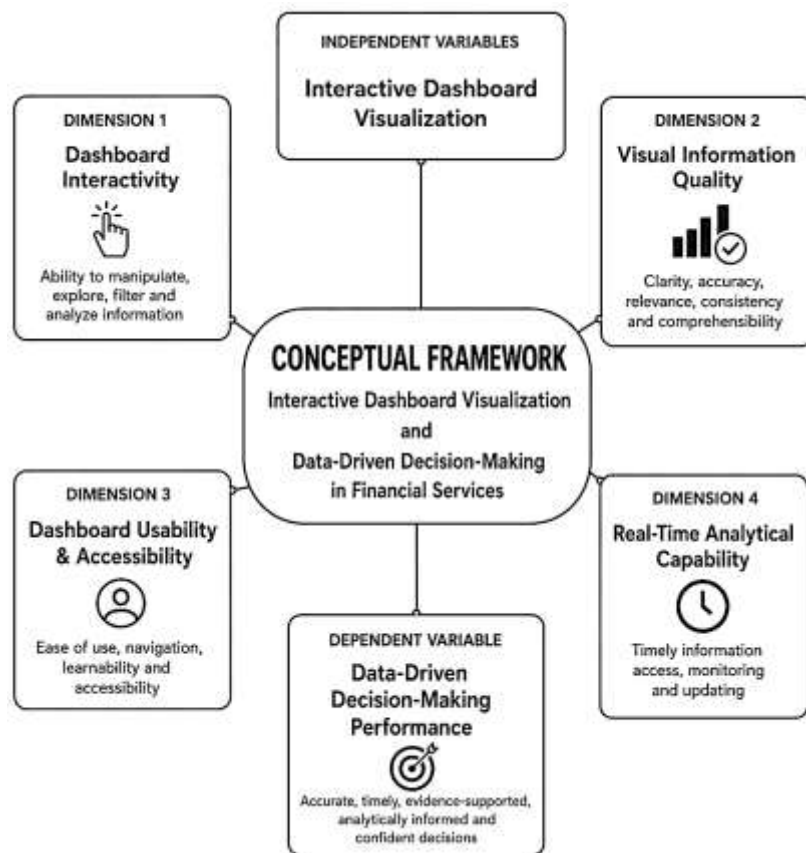
INTRODUCTION

Data visualization refers to the systematic representation of quantitative or qualitative information through graphical forms that allow users to identify patterns, comparisons, trends, relationships, anomalies, and structures that may remain difficult to recognize within raw numerical or textual datasets. In contemporary organizational information environments, interactive dashboard visualization represents a specialized application of this concept because it combines charts, indicators, performance measures, graphical interfaces, analytical controls, filters, and multidimensional displays within an integrated platform that supports the examination of organizational information. Visual representations can alter the manner in which decision makers search for information, identify relationships, compare alternatives, and process complex evidence during analytical tasks (Lurie & Mason, 2007). Interactivity adds another dimension to visualization by enabling users to select, filter, navigate, rearrange, connect, and explore information based on their immediate analytical requirements (Yi et al., 2007). Interactive visual environments therefore allow decision makers to move between overview, exploration, comparison, filtering, and detailed investigation rather than relying exclusively on predetermined and static reporting structures (Heer & Shneiderman, 2012). Organizational dashboards commonly consolidate information obtained from multiple sources while presenting summarized performance indicators, trends, targets, exceptions, and other decision-relevant measures through a single visual interface (Yigitbasioglu & Velcu, 2012). The interactive properties of visualization systems also enable users to manipulate representations of complex information according to the analytical questions being examined, creating a direct relationship between organizational datasets and human interpretation (Janvrin et al., 2014). Visualization effectiveness is consequently influenced not only by the information displayed but also by the type of visualization and the mechanisms through which users interact with the visual environment (Perkhofer et al., 2020). Within the context of the present study, interactive dashboard visualization refers to the combined ability of a dashboard to represent financial information clearly, accurately, and meaningfully while allowing users to navigate, filter, interrogate, customize, compare, and dynamically explore information in support of organizational decision activities. This definition emphasizes dashboard visualization as an analytical information-processing environment rather than merely a graphical reporting mechanism, creating a basis for examining the specific characteristics through which interactive dashboards are associated with data-driven decision-making activities in financial-service organizations.

Data-driven decision making can be understood as an organizational process through which judgments, choices, and managerial actions are systematically informed by the collection, processing, analysis, interpretation, and application of relevant data rather than being dependent primarily on intuition, unsupported assumptions, or isolated personal experience. This approach is closely associated with decision support systems, business intelligence systems, and business analytics because these technologies transform organizational data into structured information that decision makers can use when evaluating problems, alternatives, risks, and performance outcomes. Data-driven decision support systems provide technological environments through which organizational information can be accessed, analyzed, monitored, and incorporated into managerial decisions (Power, 2008). Decision support systems more broadly represent information technologies developed to strengthen decision processes by providing relevant analytical information to organizational users (Arnott & Pervan, 2008). Business intelligence systems contribute to this process by integrating data from organizational sources and transforming those data into information that can support operational and managerial decision making (Elbashir et al., 2008). The development of business intelligence and analytics has further connected data management, statistical analysis, information technologies, predictive methods, and managerial judgment within integrated organizational environments (Chen et al., 2012). The effectiveness of such systems is associated with factors including information quality, analytical culture, technological capabilities, access to information, and characteristics of the organizational decision environment (Işık et al., 2013; Popović et al., 2012). These relationships carry international significance because organizations operating across national, regulatory, institutional, and competitive environments increasingly process extensive quantities of transactional, operational, market, customer, and performance data. Research examining business intelligence value has emphasized that

technological resources must be connected with organizational processes through which analytical information is accessed and used in decision activities (Trieu, 2017). Broader reviews of business intelligence research have similarly identified adoption, utilization, system quality, information quality, organizational conditions, and successful use as major components of business intelligence effectiveness (Ain et al., 2019). Interactive dashboards occupy a particularly visible position within this analytical infrastructure because they often represent the interface through which complex organizational information is organized, summarized, examined, and interpreted by managers and analysts. Their relationship with data-driven decision making consequently depends on the quality of the information presented and the degree to which users can effectively access, understand, manipulate, and apply that information to specific organizational decisions.

Figure 1: Framework Linking Interactive Dashboard Visualization to Data-Driven Decision-Making Performance in Financial Services



The relationship between interactive visualization and data-driven decision making is especially relevant within financial services because banking, insurance, lending, investment management, accounting, auditing, financial risk management, regulatory compliance, and fintech activities depend extensively on high-volume and multidimensional information. Financial institutions continuously process customer transactions, account records, lending histories, investment information, payment activities, financial statements, risk indicators, regulatory information, market movements, operational measures, fraud signals, and customer-behavior data. Such information environments create analytical demands that may be difficult to address through static reports alone, particularly when managers and analysts must compare multiple indicators or identify abnormalities within extensive datasets. Business intelligence research in banking has documented substantial use of analytics, data mining, decision support, customer intelligence, and related analytical technologies in banking activities (Moro et al., 2015). Financial fraud detection similarly depends on analytical approaches that include classification, clustering, regression, anomaly detection, prediction, and other data-mining techniques

for recognizing suspicious financial activities (Ngai et al., 2011). Credit assessment represents another important data-dependent financial decision process because credit-scoring systems use customer and applicant characteristics to generate systematic assessments for lending-related judgments (Abdou & Pointon, 2011). Comparative research on credit-scoring methodologies has also demonstrated the extensive dependence of financial institutions on multidimensional analytical models when assessing creditworthiness and lending risk (Lessmann et al., 2015). Interactive visualization introduces a human-centered analytical layer into such data-intensive processes by allowing decision makers to visually investigate patterns, exceptions, and relationships. Interactive visualization can assist fraud-related analysis by allowing investigators to modify visual representations and examine different subsets of transactional information during analytical tasks (Dilla & Raschke, 2015). Financial management and accounting environments have also incorporated descriptive, predictive, and prescriptive analytics to support performance measurement, planning, reporting, and managerial analysis (Appelbaum et al., 2017). The relationship between business intelligence, analytics, management accounting, reporting, and organizational decision support has consequently become increasingly established within research on financial information systems (Rikhardsson & Yigitbasioglu, 2018). These characteristics make financial services particularly suitable for examining how dashboard visualization is associated with decision performance because financial decisions commonly require accuracy, timeliness, analytical comparison, risk recognition, data integrity, evidence evaluation, and rapid interpretation of changing organizational information.

The effectiveness of interactive dashboard visualization also depends on human perception, attention, cognition, information processing, usability, and the characteristics of the analytical task being performed. Accurate organizational data do not automatically produce effective judgments because decision makers must first locate, understand, compare, and interpret relevant information before incorporating it into a decision. Research in information visualization has shown that limitations in visual attention affect the effectiveness of graphical information presentation, particularly when displays contain multiple visual elements competing for user attention (Haroz & Whitney, 2012). Visualization evaluation therefore involves more than graphical appearance because analytical reasoning, user performance, communication, user experience, and task context all influence how individuals interact with visual information (Lam et al., 2012). The structure and design of visual representations can also influence how users recognize and remember information. Certain graphical characteristics have been associated with systematic differences in visualization memorability, indicating that visual composition affects users' interaction with displayed information (Borkin et al., 2013). Subsequent experimental work has further demonstrated that graphical and textual characteristics influence visualization recognition and recall (Borkin et al., 2016). Dashboard responsiveness represents another important component of interactive analysis because delays between user actions and visual responses can interfere with exploratory analytical behavior. Even relatively small increases in interactive latency have been associated with reduced exploratory activity, reduced dataset coverage, fewer observations, and lower levels of hypothesis generation during visual analysis (Liu & Heer, 2014). Cognitive research also indicates that visualization-assisted judgment reflects an interaction between visual encoding, perceptual processing, prior knowledge, task characteristics, and decision processes (Padilla et al., 2018). Experimental examination of visualization types and interaction has similarly shown that usability varies according to the alignment between visualization design, interactive functionality, and user tasks (Perkhofer et al., 2020). These research findings provide a basis for distinguishing several dimensions of interactive dashboard visualization within financial-service decision environments. Dashboard Interactivity concerns the extent to which users can manipulate and explore presented information. Visual Information Quality concerns the clarity, accuracy, relevance, consistency, and comprehensibility of displayed information. Dashboard Usability and Accessibility concern ease of navigation, learnability, accessibility, and user-oriented operation, while Real-Time Analytical Capability concerns timely information access, monitoring, updating, and examination of current financial indicators.

A central consideration in the examination of dashboard-supported financial decision making is the distinction between having access to analytical technologies and effectively using their capabilities during organizational decision processes. Business analytics systems generally combine data resources,

technological infrastructure, analytical methods, organizational routines, managerial processes, and human capabilities, while interactive dashboards provide a direct environment through which many of these resources become accessible to individual users. Dashboards have been examined as mechanisms for evaluating and managing business analytics capabilities, establishing a connection between analytical resources, information presentation, and managerial utilization (Rivera & Shanks, 2015). Organizational analytics capability itself depends on combinations of technological, data-related, managerial, and human resources rather than on the acquisition of analytical software alone (Gupta & George, 2016). Business analytics value has also been conceptualized through a sequence connecting analysis, insight, decision, and action, emphasizing the movement of information from analytical processing into organizational judgment (Seddon et al., 2017). Empirical research across organizational contexts has associated analytics capabilities with organizational knowledge, agility, process improvement, and performance-related outcomes (Côte-Real et al., 2017; Torres et al., 2018). Business analytics adoption has additionally been linked with business-process performance, reinforcing the role of analytical technologies within organizational information-processing activities (Aydiner et al., 2019). System availability, however, remains conceptually distinct from system utilization and successful analytical use because information quality, organizational conditions, user behavior, technological characteristics, and actual patterns of use represent separate dimensions of business intelligence effectiveness (Ain et al., 2019). Within financial services, these relationships direct analytical attention toward the characteristics of the dashboard interface through which financial managers, analysts, risk professionals, business intelligence specialists, and other organizational users interact with data. The present study therefore examines Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability as four explanatory dimensions of interactive dashboard visualization in relation to Data-Driven Decision-Making Performance. Data-Driven Decision-Making Performance is examined through users' perceived ability to make accurate, timely, evidence-supported, analytically informed, and confident decisions using dashboard-based financial information. The specified relationship between these constructs provides the empirical structure for measuring interactive dashboard visualization through a five-point Likert scale and statistically examining the resulting relationships through descriptive statistics, Pearson correlation analysis, and multiple regression modeling.

Background of the Study

Financial-service organizations operate in information-intensive environments in which managerial, operational, risk-related, investment, customer, and strategic decisions increasingly depend on the effective interpretation of large volumes of data. Banks, insurance companies, investment firms, lending institutions, fintech organizations, and other financial-service providers continuously generate information from transactions, customer interactions, credit activities, market movements, regulatory reporting, risk assessments, fraud-monitoring systems, and internal performance measures. Although the availability of such data creates opportunities for more evidence-based decision making, the usefulness of data depends substantially on the manner in which information is organized, presented, explored, and interpreted by organizational users. Traditional reports and static spreadsheets may provide valuable information, but they can limit the ability of decision makers to explore multidimensional relationships, investigate unusual patterns, compare alternative performance measures, or quickly identify changes occurring within complex financial environments. Interactive dashboard visualization has therefore become an important component of contemporary business intelligence and analytics systems because it combines graphical information presentation with functions such as filtering, drill-down analysis, dynamic navigation, real-time monitoring, customized views, and interactive exploration. Through these capabilities, financial professionals can examine key performance indicators, customer patterns, financial risks, operational conditions, and strategic metrics within a unified analytical environment. The effectiveness of such dashboards, however, cannot be understood solely through their technical availability because the quality of interaction between users, information, and decision tasks may determine whether dashboard systems contribute meaningfully to data-driven decision making. In particular, dashboard interactivity, visual information quality, usability and accessibility, and real-time analytical capability represent important characteristics that may shape the extent to which users can understand financial information and apply it to decisions.

Data-driven decision-making performance in this study refers to the ability of financial-service professionals to use organizational evidence to make accurate, timely, analytically informed, and confident decisions. Accordingly, this research focuses on the relationship between interactive dashboard visualization capabilities and data-driven decision-making performance within financial-service organizations. By examining users who directly interact with dashboards for professional decision activities, the study establishes a quantitative basis for evaluating how specific visualization characteristics are associated with the effectiveness of financial decision processes.

Problem Statement

Financial-service organizations have invested extensively in business intelligence systems, analytics platforms, and interactive dashboards to improve access to organizational information and support evidence-based decision making. However, the presence of dashboards within an organization does not necessarily establish that users are receiving information in a form that effectively supports their decisions. Financial decision makers frequently operate under conditions involving large data volumes, time pressure, rapidly changing indicators, regulatory requirements, risk exposure, complex customer behavior, and the need to compare multiple financial measures simultaneously. Under these conditions, dashboards that contain unclear visualizations, limited interactive functions, difficult navigation, delayed information, or poorly organized metrics may restrict users' ability to transform available data into meaningful analytical understanding. A central problem is therefore that organizations may possess substantial quantities of data and sophisticated visualization technologies while still facing uncertainty about which dashboard capabilities are most strongly associated with effective data-driven decision making. Existing dashboard systems may vary considerably in their levels of interactivity, visual information quality, usability, accessibility, and ability to provide timely analytical information. These differences may influence how financial professionals recognize patterns, evaluate alternatives, identify risk signals, interpret performance changes, and make decisions based on organizational evidence. Furthermore, evaluating dashboard effectiveness only through general user satisfaction or system adoption may provide an incomplete understanding of how specific visualization characteristics relate to decision performance. There is therefore a need for an empirical assessment that separates the major capabilities of interactive dashboard visualization and statistically examines their individual and combined relationships with data-driven decision-making performance. The present study addresses this problem by focusing specifically on Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability as explanatory constructs. Their relationships with Data-Driven Decision-Making Performance will be assessed among professionals working in financial-service environments using a quantitative, cross-sectional, case-study-based approach. This structure enables the study to determine whether particular dashboard capabilities have significant relationships with decision performance and whether the combined visualization model explains meaningful variation in data-driven financial decision making.

Purpose and Objectives of the Study

The primary objective of this research is to quantitatively evaluate the impact of interactive dashboard visualization on data-driven decision-making performance within financial-service organizations by examining the specific technological and information-related characteristics through which dashboards support professional decision activities. To accomplish this primary objective, the study seeks to assess the perceived effectiveness and utilization of interactive dashboards among financial-service professionals and determine how users evaluate the principal characteristics of the dashboard environments with which they interact. More specifically, the research aims to measure the level of Dashboard Interactivity available to users, including their ability to filter, navigate, explore, compare, and investigate financial information according to specific analytical requirements. The study also aims to assess Visual Information Quality by examining whether dashboard information is perceived as clear, accurate, relevant, consistent, understandable, and appropriately organized for financial analysis. A further objective is to evaluate Dashboard Usability and Accessibility in relation to ease of navigation, user friendliness, learnability, availability of relevant information, and the effort required to perform dashboard-based analytical tasks. The research additionally seeks to evaluate Real-Time Analytical Capability by examining the extent to which dashboards provide timely updates, current indicators, rapid access to relevant information, monitoring capabilities, and support for responding to changing

financial conditions. Beyond describing these constructs, the study aims to determine the direction and strength of the relationships between each interactive dashboard visualization dimension and Data-Driven Decision-Making Performance through correlation analysis. It further seeks to establish the individual and combined predictive effects of the four dashboard visualization constructs through multiple regression modeling. Data-Driven Decision-Making Performance will be evaluated through dimensions including decision accuracy, timeliness, confidence, analytical support, evidence utilization, and overall decision effectiveness. Through these objectives, the study will provide a structured statistical examination of the relationships proposed in the conceptual framework and generate empirical evidence for testing the corresponding research hypotheses within the selected financial-service context.

The research hypotheses have been developed to statistically examine the proposed relationships between the major dimensions of interactive dashboard visualization and Data-Driven Decision-Making Performance in financial-service organizations. The first hypothesis, H1, proposes that Dashboard Interactivity has a positive and statistically significant effect on Data-Driven Decision-Making Performance. This hypothesis reflects the expectation that financial professionals who can actively filter, navigate, drill down, compare, and explore dashboard information will report stronger decision performance. The second hypothesis, H2, proposes that Visual Information Quality has a positive and statistically significant effect on Data-Driven Decision-Making Performance, based on the expectation that clear, accurate, relevant, consistent, and understandable visual information facilitates the interpretation of complex financial data. The third hypothesis, H3, states that Dashboard Usability and Accessibility have a positive and statistically significant effect on Data-Driven Decision-Making Performance. This relationship assumes that dashboards that are easier to access, learn, navigate, and operate provide users with a more effective environment for applying information to organizational decisions. The fourth hypothesis, H4, proposes that Real-Time Analytical Capability has a positive and statistically significant effect on Data-Driven Decision-Making Performance, reflecting the importance of timely information, current indicators, dynamic monitoring, and rapid analytical access within financial-service environments. The fifth hypothesis, H5, proposes that Interactive Dashboard Visualization capabilities collectively have a positive and statistically significant effect on Data-Driven Decision-Making Performance. This final hypothesis evaluates the combined explanatory strength of Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability within a single regression model. These hypotheses provide a direct statistical structure for the empirical investigation and will be tested using data collected through a five-point Likert-scale questionnaire. Pearson correlation analysis will establish the direction and strength of associations, while multiple regression analysis will determine the relative contribution and statistical significance of each predictor in explaining variations in Data-Driven Decision-Making Performance.

LITERATURE REVIEW

The literature on interactive dashboard visualization and data-driven decision making encompasses several interconnected areas of research, including information visualization, business intelligence, decision support systems, financial analytics, dashboard design, human-computer interaction, information quality, usability, real-time analytics, and organizational decision performance. Interactive dashboards represent an important interface between organizational data and human decision makers because they combine visual representation with analytical interaction, allowing users to examine complex information through filtering, comparison, navigation, drill-down functions, and dynamic exploration. Within financial services, these capabilities are particularly relevant because organizational users must interpret large amounts of transactional, operational, customer, risk, regulatory, and market-related information while making decisions that frequently require accuracy and timely analysis. The literature therefore needs to address both the technological characteristics of dashboard systems and the cognitive and organizational conditions through which those characteristics become connected to decision-making activities. This review organizes the existing knowledge around the principal constructs used in the present study. It first examines interactive dashboard visualization and business intelligence within financial-service environments, establishing the broader technological and organizational context of dashboard-based analytics. It then considers

dashboard interactivity and data exploration as mechanisms through which users actively investigate financial information. Visual Information Quality, Dashboard Usability and Accessibility are examined in relation to information clarity, accuracy, relevance, navigation, accessibility, and user interaction. Real-Time Analytical Capability is subsequently considered in relation to timely information processing and the monitoring of changing financial indicators. The review also establishes Task-Technology Fit Theory as the principal theoretical framework for explaining the correspondence between dashboard capabilities and financial decision requirements. Finally, the conceptual framework integrates Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability as explanatory variables associated with Data-Driven Decision-Making Performance, providing the theoretical and empirical structure for the hypotheses examined in the quantitative analysis.

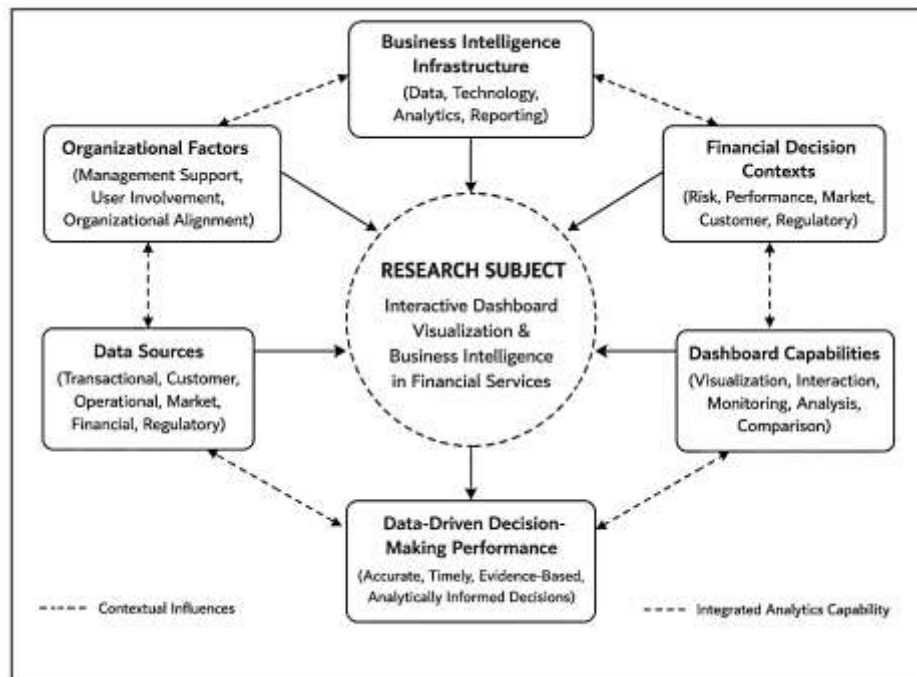
Interactive Dashboard Visualization in Financial Services

Interactive dashboard visualization has become an important component of business intelligence in financial services because it provides a structured interface through which complex financial information can be organized, monitored, compared, and explored. Business intelligence refers to the coordinated use of data repositories, analytical technologies, reporting systems, and decision-support processes to convert organizational data into information that can guide managerial action. Within banks, insurers, investment firms, lending institutions, and other financial organizations, this function is especially important because decision makers work with high volumes of transactional, customer, risk, operational, market, and regulatory information. Interactive dashboards extend conventional reporting by presenting these data through visual elements such as charts, key performance indicators, trend displays, scorecards, alerts, and comparative measures while allowing users to modify the presentation according to their analytical needs. The success of business intelligence in financial services is therefore closely connected with the quality of the technological environment, the availability of appropriate data, management support, user involvement, and alignment between analytical systems and organizational requirements. Research conducted within the South African financial-services sector identified several critical success factors for business intelligence initiatives, emphasizing that technological capability must operate together with organizational and human conditions for BI projects to produce useful decision information (Dawson & Belle, 2013; Debasish, 2021). Business intelligence quality is also associated with the capacity of organizations to strengthen diagnostic and interactive performance measurement, particularly when BI systems provide integrated infrastructure, appropriate functionality, and self-service capabilities that allow decision makers to interact directly with performance information (Abdur & Iftekhhar, 2021; Peters et al., 2016). Interactive dashboards can consequently be viewed as an operational layer of business intelligence through which financial professionals translate integrated organizational data into visible, navigable, and decision-relevant representations, linking underlying analytical infrastructure with the practical information requirements of managers and analysts. This connection remains central to evaluating dashboard-supported financial decision processes.

The financial-services context places strong demands on dashboards because financial decisions often require simultaneous attention to accuracy, timeliness, risk exposure, performance variation, customer behavior, and changing market conditions. A dashboard designed for this environment must do more than display information; it must allow users to identify relevant indicators quickly, move between summary and detailed views, investigate deviations, compare alternatives, and understand the relationships among multiple measures. Interactive features such as filtering, drill-down, scenario adjustment, sorting, highlighting, and what-if analysis can make financial information more responsive to the specific task. These functions are important because the same dataset may need to support different decisions across credit management, portfolio monitoring, liquidity control, fraud detection, customer analysis, branch performance, regulatory reporting, or executive oversight. Experimental research on interactive analytical dashboards has shown that dashboard features can influence situation awareness and task performance, with what-if functionality enabling users to participate more directly in analytical problem solving rather than relying only on static system outputs (Debasish, 2022; Nadj et al., 2020). This relationship between interaction and decision support is consistent with the broader role of business intelligence in commercial banking, where analytical systems have been

evaluated in connection with financial condition and management performance. Evidence from commercial banks indicates that the implementation and use of BI systems can be examined through changes in financial indicators, comparative performance, and organizational conditions, demonstrating the integration of analytics into banking management (Ashfaq & Mohammad, 2022; Tunowski, 2020). For financial-service organizations, interactive dashboard visualization therefore represents a point of convergence between data management, analytical processing, performance monitoring, and managerial interpretation. Its value depends on whether dashboard content is relevant to the decision context, whether users can explore that content efficiently, and whether the visual interface supports movement from raw indicators toward recognizable financial patterns, exceptions, comparisons, and relationships that can be incorporated into organizational judgment.

Figure 2: Interactive Dashboard Visualization and Business Intelligence Framework for Data-Driven Decision-Making in Financial Services



Business intelligence and interactive dashboard visualization should be understood as an organizational analytics capability rather than isolated reporting technology. Contemporary BI environments combine structured and unstructured data, analytical models, visual interfaces, self-service tools, and increasingly distributed information sources, with dashboards serving as principal user-facing mechanisms for analytical outputs. A systematic examination of business intelligence and analytics research has shown that the field has expanded across multiple data types, technologies, analytical methods, organizational applications, and user contexts, reflecting a shift from traditional reporting toward more diverse and interactive forms of analytical information use (Eggert & Alberts, 2020; Sheak & Risha, 2022). In financial services, this broad analytical environment is visible in the way organizations integrate transaction systems, customer databases, risk models, accounting information, market feeds, and operational records into centralized or connected business intelligence architectures. Dashboards provide a means of presenting selected outputs from these systems in a form that supports repeated monitoring and exploratory analysis without requiring every user to engage directly with underlying databases or technical analytical procedures. This feature is particularly relevant for managers and professionals whose decision responsibilities require rapid access to interpretable evidence but who may differ considerably in technical expertise. The effectiveness of dashboard-based BI therefore depends on the relationship between data integration, information presentation, interactive functionality, user accessibility, and the decision task itself. For the present study, this

relationship is operationalized through four core dimensions: Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability. These dimensions capture how financial professionals engage with dashboard systems, how clearly information is presented, how easily the system can be used, and how promptly relevant information can be accessed. Examining these dimensions together provides a focused basis for evaluating interactive dashboard visualization as a business-intelligence mechanism within financial services and for determining how its characteristics relate to Data-Driven Decision-Making Performance.

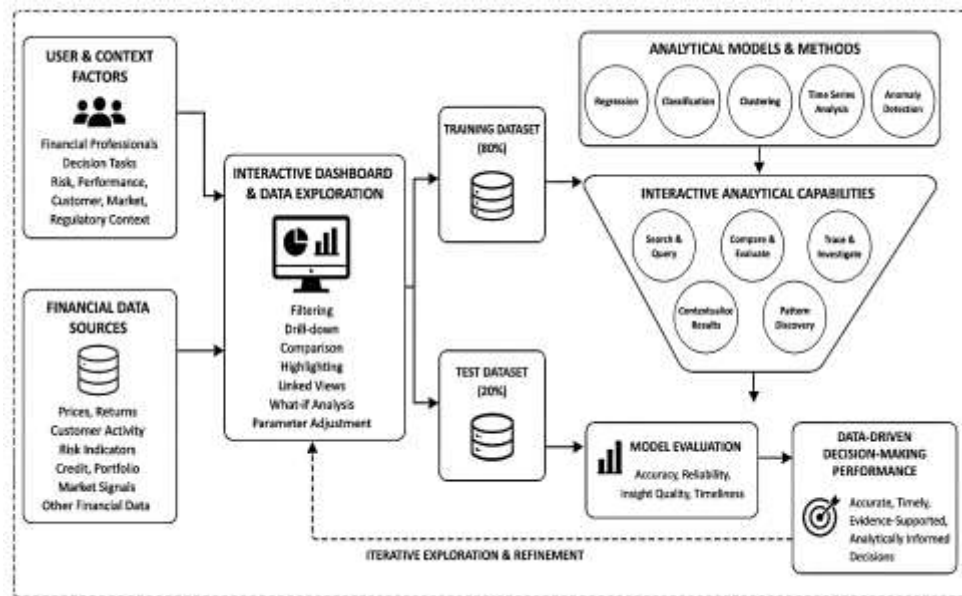
Dashboard Interactivity for Financial Decision Making

Dashboard interactivity refers to the capacity of users to actively manipulate, interrogate, reorganize, and explore visualized information rather than receive information through a fixed display. Within financial decision environments, this capability is particularly important because professionals routinely work with multidimensional datasets that include prices, returns, customer activity, risk measures, credit indicators, portfolio positions, liquidity measures, operating results, and market signals. Interactive exploration allows users to move from an overall view of performance to narrower subsets of information, compare selected entities, identify unusual observations, and test alternative interpretations of changing financial conditions. Such processes transform visualization from a passive reporting mechanism into an analytical environment in which the user controls the sequence and depth of investigation. Research on financial time-series visualization has demonstrated the usefulness of combining automated analytical methods with interactive graphical exploration for examining large volumes of time-varying financial indicators, particularly when users need to recognize clusters, trajectories, similarities, and deviations that are difficult to interpret through conventional tables alone ([Rashedul & Kaium, 2022](#); [Schreck et al., 2007](#)). Financial decision making also involves judgments about accuracy and confidence, which makes the design of interactive representations consequential to how users evaluate evidence. Experimental research examining interactive financial visualizations found that visualization and interactivity can influence the calibration between decision accuracy and confidence, showing that the form and interactive properties of financial information can affect how users understand their judgments ([Rashedul & Kaium, 2022](#); [Tang et al., 2014](#)). For dashboard users in financial services, interactivity may therefore include filtering, drill-down functions, highlighting, selection, linked views, comparative displays, parameter adjustment, and other mechanisms that allow information to be examined according to the requirements of a decision. These capabilities provide the analytical foundation for investigating how dashboard interactivity is related to data-driven decision-making performance. This user-directed exploration is especially relevant when financial evidence must be reviewed across organizational levels and contexts.

Data exploration through interactive dashboards is also closely connected with the sequence through which financial users develop, refine, and evaluate analytical understanding. Financial decisions rarely depend on a single isolated indicator; users frequently need to investigate relationships among measures, examine the origin of an unexpected value, compare historical and current conditions, and determine whether an observed pattern is meaningful or temporary. Interactive visualization supports this process by allowing users to formulate questions through direct engagement with data and to modify the displayed information as new observations emerge. Enterprise research involving analysts from multiple industries, including finance, has shown that organizational analysis is iterative and involves repeated movement among data acquisition, transformation, exploration, visualization, model development, and communication. The study also identified barriers associated with data quality, tool limitations, organizational context, and the movement between analytical systems, demonstrating that effective exploration depends on both technical functionality and the wider environment of use ([Kandel et al., 2012](#); [Chowdhury & Tonay, 2022](#)). The value of interaction is especially evident in investment-related settings, where users often need to locate and integrate dispersed pieces of financial information before reaching a judgment. Experimental evidence comparing interactive financial data with conventional reporting formats has examined how retail investors locate, combine, and apply accounting information when making investment decisions, illustrating that interactivity must be evaluated in relation to the actual information-integration task rather than assumed to improve every decision automatically ([Locke et al., 2015](#); [Hossan, 2022](#)).

For financial dashboards, this perspective means that interactive functions should be understood according to the analytical activities they enable, including search, comparison, filtering, contextualization, tracing, and investigation. Dashboard interactivity is therefore closely associated with the user's capacity to convert a broad financial information environment into a focused sequence of evidence relevant to a specific decision problem. This interaction supports narrower examination without disconnecting users from the broader context.

Figure 3: Interactive Dashboard and Data Exploration Framework for Data-Driven Financial Decision-Making Performance



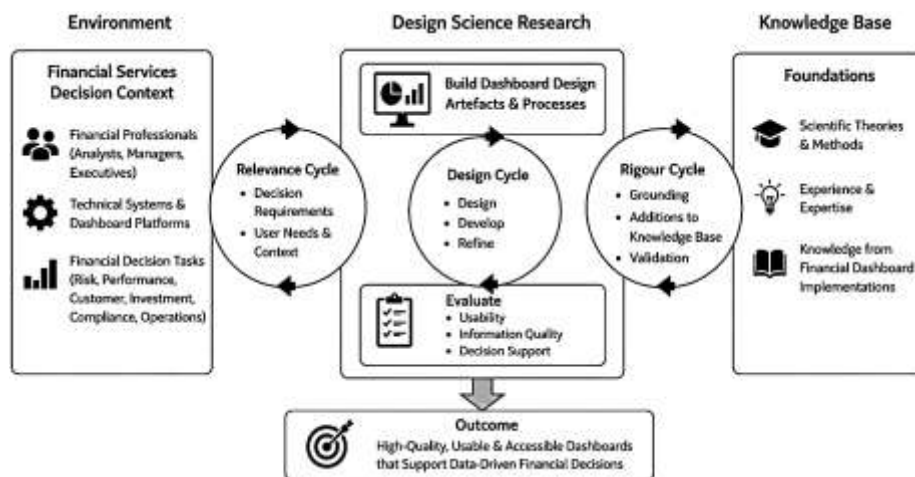
Interactive exploration becomes particularly significant when financial professionals must monitor systems in which risk, performance, and institutional relationships change across multiple dimensions. Financial stability analysis illustrates this requirement because analysts may need to evaluate institutions, markets, exposures, liquidity conditions, interconnected risks, and emerging stresses using heterogeneous data collected from different sources. In such environments, static visualization can summarize known information, while visual analytics adds a continuing interaction cycle in which users refine queries, modify perspectives, combine automated analysis with domain knowledge, and investigate patterns that emerge during exploration. Research on financial stability monitoring has described visual analytics as the integration of analytical reasoning, interactive visualization, and computational analysis, emphasizing its relevance for tasks such as maintaining situational awareness, identifying potential sources of instability, examining large dynamic datasets, and converting complex information into knowledge that can support financial supervision and policy decisions (Flood et al., 2016; Nishat & Kaniz, 2022). The same analytical logic can be transferred to organizational financial-service dashboards because managers and analysts also work with combinations of indicators rather than fixed information requirements. A risk manager may filter exposures by customer category, geography, or product; a lending manager may drill from portfolio-level indicators to individual borrower segments; an investment professional may compare performance patterns across instruments; and an operations manager may isolate changes in transactions, service volumes, or exceptions. These examples demonstrate that dashboard interaction is not simply a technical feature but a structured mechanism for directing attention and controlling the scope of analysis. In this study, Dashboard Interactivity is treated as an explanatory construct representing the extent to which users can manipulate, navigate, filter, compare, and investigate dashboard information. Its relationship with Data-Driven Decision-Making Performance is examined on the basis that effective exploration enables financial professionals to align information with analytical questions, evidence requirements, and

judgment processes involved in organizational decisions.

Visual Information Quality and Accessibility

Visual Information Quality is a central dimension of interactive dashboard effectiveness because financial professionals depend on representations that are accurate, clear, relevant, consistent, complete, and understandable when interpreting complex data. Within financial services, the quality of visualized information determines whether users can distinguish patterns from irrelevant detail, recognize deviations in performance, compare financial indicators, and connect displayed evidence with a specific decision problem. A dashboard may contain technically correct data yet remain difficult to use if visual elements are poorly structured, labels are ambiguous, comparisons are visually inconsistent, or essential context is missing. Information visualization research has emphasized that effective systems should assist users in overcoming analytic gaps between lower-level data representation and higher-level reasoning tasks such as explanation, comparison, causal interpretation, and decision making (Amar & Stasko, 2005; Shaiful et al., 2022). This perspective is especially relevant to banking, insurance, investment, lending, and risk-management environments because users often examine numerous indicators simultaneously and must determine which information deserves attention. Visual Information Quality therefore extends beyond graphical attractiveness and includes the degree to which a dashboard presents decision-relevant information in an interpretable form. Appropriate chart selection, readable scales, meaningful labels, logical grouping, consistent formatting, sufficient contextual detail, and accurate representation can reduce ambiguity when users examine financial performance. Poor visualization quality, by contrast, can increase the effort required to decode information and may make comparisons more difficult. For the present study, Visual Information Quality represents users' perceptions that dashboard information is clearly presented, accurate, relevant to their responsibilities, sufficiently complete, logically organized, and consistent across displays. Treating this construct separately from interactivity is important because users may be able to manipulate a dashboard extensively while still receiving visually confusing or inadequately organized information. The quality of the visual representation therefore forms a distinct analytical condition through which dashboard information becomes suitable for data-driven financial judgment. Dashboard Usability and Accessibility represent the extent to which financial-service professionals can access, understand, navigate, and operate dashboard functions while performing analytical tasks. Usability concerns the ease with which users can learn the system, locate required information, understand controls, move between views, interpret feedback, and complete tasks without unnecessary cognitive or procedural burden. Accessibility in the present context refers to the availability of dashboard information to authorized users and the ease with which relevant analytical content can be reached across work settings. These characteristics are important because technically advanced business intelligence systems may remain underused when users encounter confusing navigation, excessive complexity, unfamiliar terminology, poorly organized menus, or difficult interaction sequences. Research evaluating business intelligence applications has identified usability as an important condition affecting the effective use and benefit of BI systems and has emphasized the need to adapt usability criteria to the specific characteristics of analytical applications (Jooste et al., 2014). Eye-tracking research on business intelligence interfaces has likewise shown that usability problems can be investigated through observable user behavior, reinforcing the importance of incorporating usability assessment within the BI lifecycle rather than treating it as a secondary design concern (Beelders & Kotzé, 2020). In financial services, these issues can become significant because users may differ in technical expertise while sharing responsibility for interpreting time-sensitive business information. A risk analyst, branch manager, financial controller, investment specialist, or executive may require different levels of analytical detail, yet each must be able to locate and interpret relevant information efficiently. Dashboard Usability and Accessibility therefore encompass intuitive navigation, understandable controls, logical layout, ease of learning, responsive interaction, retrieval of needed information, and ready availability during decision activities. These characteristics determine whether dashboard functionality can be translated into analytical use rather than remaining technically available but operationally difficult for financial decision makers to employ.

Figure 4: Design Science Research Framework for Visual Information Quality, Dashboard Usability, and Accessibility



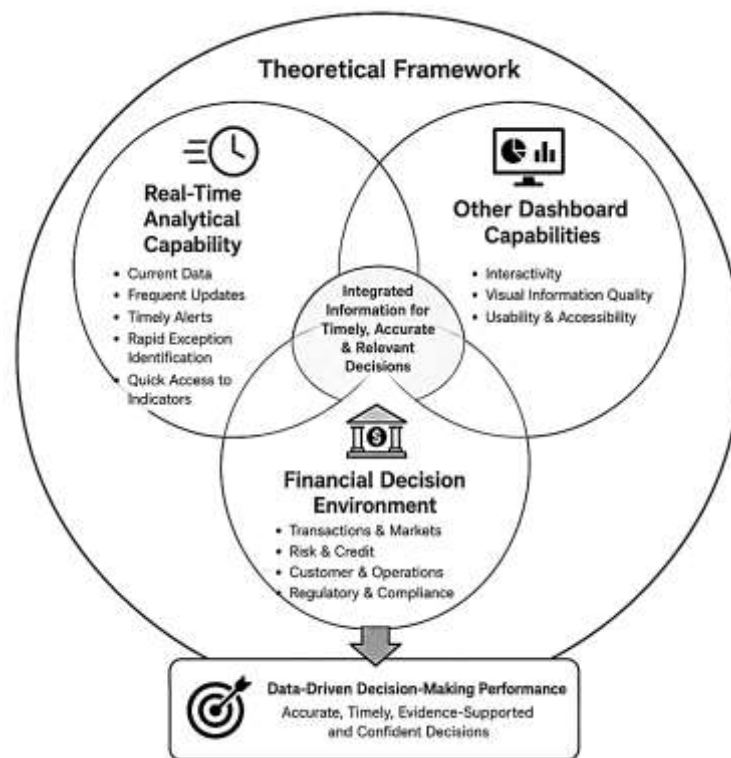
Visual information quality, usability, and accessibility become clearer when dashboards are considered organizational decision interfaces rather than reporting screens. A dashboard synthesizes data from multiple systems and presents measures to users who must decide where to focus attention, how to interpret relationships, and whether the displayed evidence is sufficient for action. Dashboard quality therefore depends on the information presented and the ease with which users engage with it. Cross-sectional evidence from managers using corporate dashboards has shown that dashboard quality and dashboard information are associated with the extent of dashboard use, while strategy alignment and interactive management control are connected with perceived managerial and organizational performance (Reinking et al., 2020). This relationship illustrates why financial dashboards should provide information that is not only coherent but also aligned with the responsibilities of users. Evidence from visualization-based decision research also indicates that decision makers' use of visualizations is associated with decision-making success and that familiarity with visual representations shapes how effectively visual information is employed (Killen et al., 2020). In finance, familiarity and usability can affect the interpretation of profitability measures, credit indicators, customer trends, risk exposures, investment performance, or operational exceptions because the same underlying data can create levels of understanding depending on how they are presented and accessed. For this study, Visual Information Quality and Dashboard Usability and Accessibility are therefore treated as separate but related explanatory constructs. The first captures the quality of the information representation, while the second captures the perceived ease with which users can reach, navigate, and operate the dashboard environment. Their inclusion allows the empirical model to distinguish whether data-driven decision-making performance is associated primarily with what financial dashboards communicate, with how easily users can engage with them, or with the combined presence of high-quality visual information and usable analytical access during organizational decision activities.

Data-Driven Decision-Making Performance

Real-Time Analytical Capability refers to the capacity of an information system to capture, integrate, process, update, and present decision-relevant data with sufficiently low latency for users to respond to current organizational conditions. In financial services, this capability is particularly important because many decisions are connected with rapidly changing information relating to transactions, liquidity, credit exposure, customer behavior, fraud alerts, portfolio movements, market prices, operational exceptions, and regulatory indicators. Traditional business intelligence commonly relies on periodically refreshed data warehouses and scheduled reports, which may create a temporal separation between the occurrence of an event and its visibility to decision makers. Real-time business intelligence reduces this separation by combining continuous or frequent data acquisition with analytical processing and rapid information delivery. Early work on real-time BI emphasized the movement from historical analysis toward systems capable of analyzing current data and supporting immediate

responses to changing business conditions, thereby linking analytical output more directly with operational processes (Azvine et al., 2005). The practical significance of this capability was also demonstrated through enterprise implementations in which real-time data warehousing was used to support tactical decisions and operational actions through timely access to integrated information (Watson et al., 2006). For financial-service organizations, the same logic applies when decision makers monitor key performance indicators, transaction streams, credit portfolios, customer activities, or risk measures whose relevance may decline if information becomes outdated. A dashboard with strong real-time analytical capability should therefore provide current data, frequent refreshes, timely alerts, rapid identification of exceptions, and accessible performance indicators without requiring users to wait for lengthy reporting cycles. In this study, Real-Time Analytical Capability is treated as a distinct dimension of interactive dashboard visualization because timeliness influences whether visualized information reflects the decision environment at the moment when financial professionals must evaluate alternatives, detect problems, or select actions in practice.

Figure 5: Real-Time Analytical Capability Framework for Data-Driven Decision-Making Performance



Real-time analytical capability is also connected with the quality of managerial decision making because timely information has limited value when it is incomplete, poorly integrated, or difficult to interpret. Business intelligence systems create decision support through the interaction of data quality, analytical scope, system management, and information delivery rather than through speed alone. Empirical research examining BI management and managerial decision quality has shown that the quality of BI management is related to decision quality both directly and indirectly through data and information quality and the scope of BI solutions, demonstrating that analytical resources must be organized effectively before they can strengthen managerial judgment (Wieder & Ossimitz, 2015). This relationship is relevant to interactive financial dashboards because real-time functionality should provide decision makers with information that is not only current but also accurate, coherent, relevant, and integrated for meaningful analysis. A credit-risk dashboard, for example, may update frequently, yet rapid refresh rates offer limited analytical benefit if borrower information is inconsistent across systems or if key indicators cannot be compared. Similarly, an investment dashboard may display

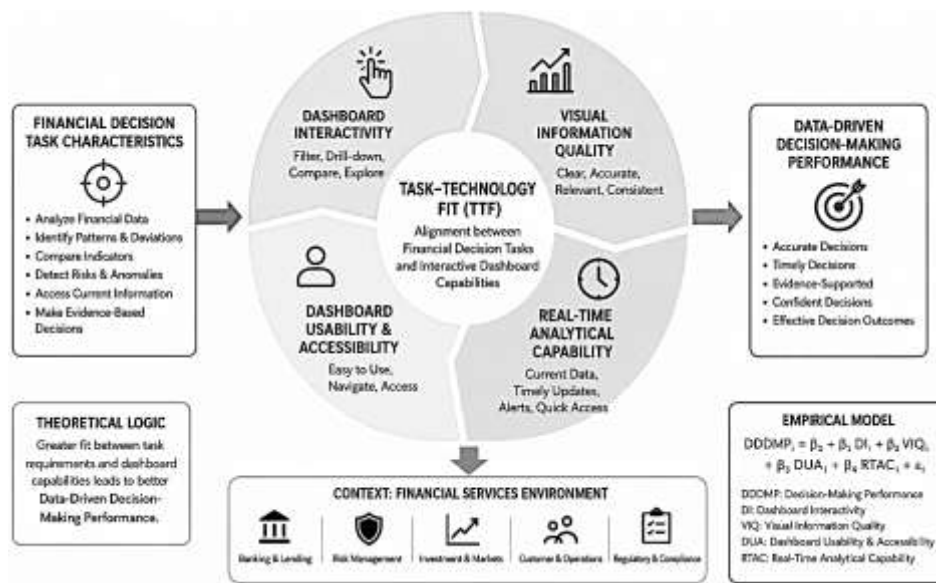
current market movements, but decision makers still require appropriate historical context, benchmarks, risk measures, and portfolio relationships to interpret those changes. Real-time analytical capability should therefore be viewed as a coordinated process involving data capture, transformation, integration, analysis, visualization, and user access. In financial institutions, the capability may support monitoring of payment activity, unusual transactions, exposure concentrations, branch performance, customer behavior, service disruptions, liquidity positions, or market-sensitive indicators. When these data are integrated into interactive dashboards, users can combine current information with filters, comparisons, drill-down functions, and graphical representations that make changing conditions easier to investigate. This combination connects the temporal quality of information with the analytical activities through which financial professionals convert dashboard outputs into evidence used for organizational judgment and data-driven decisions.

The relationship between real-time analytics and Data-Driven Decision-Making Performance becomes clearer when business intelligence is considered as a decision-support capability rather than a reporting mechanism. Decision performance depends on the extent to which users can identify a relevant issue, obtain suitable evidence, interpret that evidence, compare possible responses, and act within the time available. Research examining business intelligence functions has found significant relationships between BI capabilities, decision-support benefits, and organizational benefits, indicating that analytical functionality can shape the quality and usefulness of information available within decision environments (Rouhani et al., 2016). Business intelligence systems also contribute to organizational knowing by supporting practices such as problem articulation and data selection, through which users identify questions and select information for managerial requirements (Shollo & Galliers, 2016). These processes matter in financial services because analytical evidence depends on relevance and timing. A fraud signal that becomes visible after a substantial delay, a liquidity indicator based on outdated transactions, or a customer-risk measure that is not refreshed when conditions change may provide weaker support for immediate decisions. Real-time dashboards can reduce this problem by presenting updated indicators and allowing authorized users to investigate emerging changes while retaining access to contextual information. Here, Real-Time Analytical Capability represents users' perceptions that dashboard information is updated promptly, reflects current operating conditions, provides timely monitoring of important indicators, enables rapid access to decision-relevant data, and supports quick investigation of changes or exceptions. Its proposed relationship with Data-Driven Decision-Making Performance concerns whether greater analytical timeliness is associated with more accurate, timely, evidence-supported, and confident decisions. Treating this capability as an independent construct also permits the empirical analysis to distinguish the influence of information timeliness from Dashboard Interactivity, Visual Information Quality, and Dashboard Usability and Accessibility within the multiple regression model used to evaluate interactive dashboard visualization in financial-service organizations.

Task-Technology Fit Theory

Task-Technology Fit Theory provides a suitable theoretical foundation for examining interactive dashboard visualization in financial services because it explains technology effectiveness through the correspondence between the capabilities of an information system and the requirements of the tasks performed by its users. The central premise is that technology contributes more strongly to performance when its functions match the information-processing, analytical, and operational demands embedded within a particular task. In financial-service environments, decision tasks frequently require users to interpret large quantities of transactional, customer, market, credit, risk, and operational information under conditions of time pressure and uncertainty. An interactive dashboard therefore becomes valuable when its technological characteristics support these requirements through filtering, drill-down analysis, visual comparison, rapid navigation, timely updating, and accessible presentation of decision-relevant information. Research extending Task-Technology Fit has shown that the level of fit between technological capabilities and task requirements can vary from under-fit to ideal fit, and that these differences are associated with individual performance during technology-supported activities (Junglas et al., 2008). Related evidence has also demonstrated that task-technology fit can influence performance, while the manner in which users appropriate and adapt technology may modify the strength of this relationship across repeated tasks (Fuller & Dennis, 2009).

Figure 6: Task-Technology Fit Theory Framework for Interactive Dashboard-Enabled Data-Driven Decision Making



Applied to the present study, the relevant task characteristics include the need to identify financial patterns, compare performance indicators, detect anomalies, investigate risk signals, access current information, and make evidence-based judgments. The corresponding dashboard characteristics are represented by Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability. The theoretical relationship is represented below, where TTF denotes task-technology fit, TC represents financial decision-task characteristics, and DC represents interactive dashboard capabilities. Higher correspondence between these elements indicates stronger fit and a more supportive analytical environment for data-driven financial decision making within contemporary financial-service organizations examined.

$$TTF = f(TC, DC)$$

Task-Technology Fit is relevant to dashboard-based financial analysis because the technological capability may produce different performance outcomes across decision tasks or user contexts. A dashboard effective for routine branch-performance monitoring may not provide equivalent fit for portfolio-risk assessment, fraud investigation, liquidity monitoring, or investment analysis because each activity places different demands on information detail, timeliness, interaction, comparison, and interpretation. Research on managerial information systems has emphasized that fit must account for the relationship among managerial tasks, technological functionality, and the context in which technology is used, with effective fit expected to support stronger task performance (Gebauer et al., 2010). Research on forecasting support systems similarly demonstrates that performance depends on the alignment among system characteristics, user access, procedures, and the forecasting activities that the technology is intended to support (Smith & Mentzer, 2010). This logic provides a direct theoretical justification for examining dashboard characteristics as separate explanatory dimensions rather than treating interactive visualization as a single undifferentiated technology. Dashboard Interactivity reflects whether users can manipulate information according to task requirements; Visual Information Quality reflects whether the representation communicates relevant financial evidence clearly and accurately; Dashboard Usability and Accessibility reflect whether users can reach and operate required functions with reasonable effort; and Real-Time Analytical Capability reflects whether information is available within the time conditions of the decision. In Task-Technology Fit terms, each dimension represents a technological characteristic whose value depends on the extent to which it supports the financial task being undertaken. The theory therefore links technical characteristics with performance through functional correspondence rather than through technology availability alone. For this research, perceived fit is expected to be reflected indirectly when respondents report that dashboard capabilities

assist them in completing analytical tasks accurately, efficiently, confidently, and on the basis of appropriate organizational evidence, thereby connecting the theoretical framework with Data-Driven Decision-Making Performance.

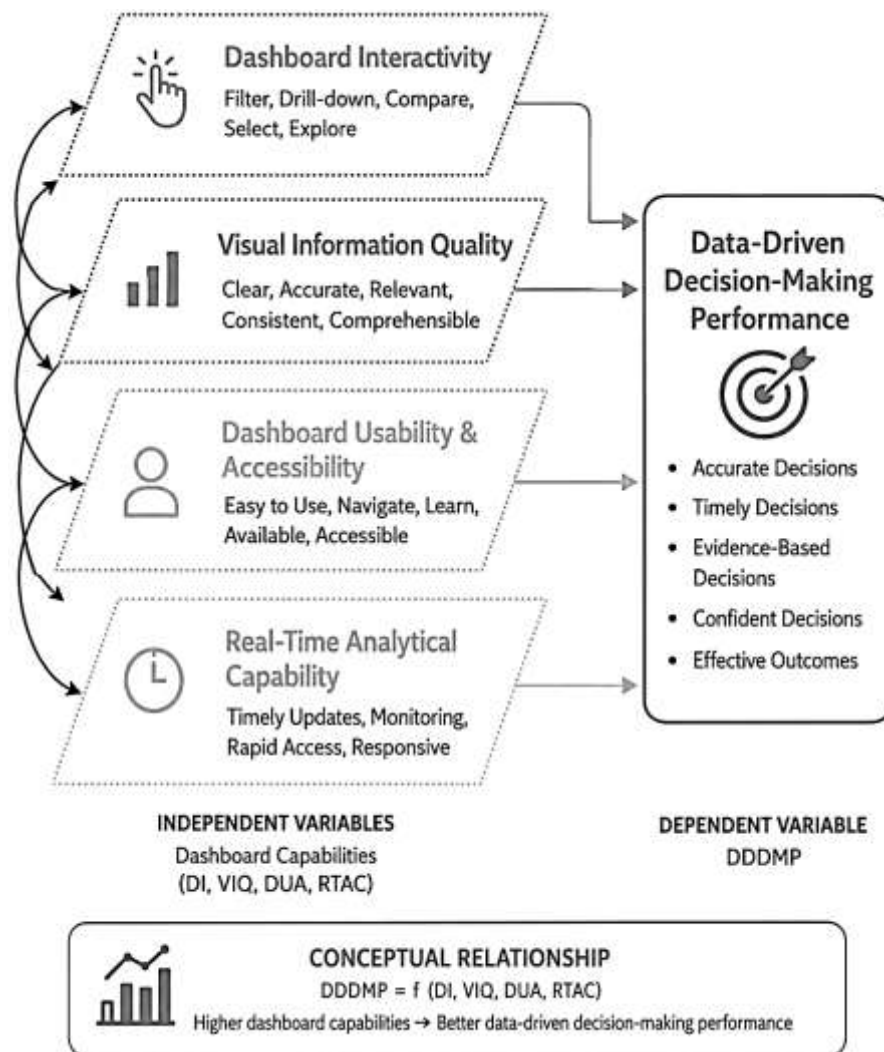
The theoretical logic of Task-Technology Fit also provides the basis for the quantitative model throughout this study. Decision-support research has shown that performance is affected by interaction between task and technology and that technological performance can serve as a precursor to successful task performance, reinforcing the need to evaluate information systems according to how effectively their characteristics support the work users must perform (Parkes, 2013). In the present financial-services context, the dependent construct, Data-Driven Decision-Making Performance, represents perceived accuracy, timeliness, confidence, analytical support, evidence utilization, and effectiveness in decisions made with dashboard information. The four independent constructs represent technological capabilities that are expected to strengthen this performance when they correspond with the demands of financial analysis. The study therefore operationalizes the Task-Technology Fit logic through the multiple regression equation below. $DDDMP_i$ denotes Data-Driven Decision-Making Performance for respondent i , DI_i denotes Dashboard Interactivity, VIQ_i denotes Visual Information Quality, DUA_i denotes Dashboard Usability and Accessibility, $RTAC_i$ denotes Real-Time Analytical Capability, β_0 is the intercept, β_1 through β_4 are regression coefficients, and ε_i represents unexplained variation. This equation is the principal formula that will be applied throughout the empirical study because it tests whether dashboard capabilities derived from the theoretical framework explain variation in decision performance. Descriptive statistics will establish the perceived level of each construct, correlation analysis will determine the direction and strength of bivariate relationships, and multiple regression will estimate the unique contribution of each dashboard capability while controlling for the others. The framework therefore provides a coherent theoretical connection among dashboard technology characteristics, financial decision-task requirements, the five hypotheses, and the statistical analyses used to evaluate the proposed relationships. This structure also permits direct evaluation of both individual predictor effects and overall explanatory strength of the integrated dashboard model.

$$DDDMP_i = \beta_0 + \beta_1 DI_i + \beta_2 VIQ_i + \beta_3 DUA_i + \beta_4 RTAC_i + \varepsilon_i$$

Conceptual Framework

The conceptual framework of this study integrates interactive dashboard visualization capabilities with Data-Driven Decision-Making Performance in financial services by treating the dashboard as a user-facing analytical system through which organizational data are transformed into decision-relevant evidence. The framework distinguishes four explanatory constructs: Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability. These constructs represent different but complementary characteristics of the dashboard environment. Dashboard Interactivity captures the ability to filter, drill down, compare, select, and explore financial information; Visual Information Quality captures clarity, accuracy, relevance, consistency, and comprehensibility; Dashboard Usability and Accessibility capture ease of navigation, learnability, availability, and operational simplicity; and Real-Time Analytical Capability captures timely updating, monitoring, rapid access, and responsiveness to changing conditions. Dashboard research has emphasized that effective dashboards integrate critical metrics into a consolidated display and that their usefulness depends on choices concerning content, design, deployment, and use in managerial decision processes (Pauwels et al., 2009). Information-systems research similarly indicates that system quality and information quality shape user evaluations of technological environments and can influence subsequent beliefs about usefulness and ease of use (Wixom & Todd, 2005). In the present study, these relationships are expressed conceptually by the function below, where $DDDMP$ denotes Data-Driven Decision-Making Performance, DI represents Dashboard Interactivity, VIQ denotes Visual Information Quality, DUA represents Dashboard Usability and Accessibility, and $RTAC$ denotes Real-Time Analytical Capability. The framework therefore assumes that stronger dashboard capabilities are associated with stronger perceived decision performance when financial professionals use dashboards to interpret evidence, compare alternatives, recognize changes, and support work-related judgments.

Figure 7: Framework Linking Interactive Dashboard Visualization to Data-Driven Decision-Making Performance



This specification provides a direct bridge between the theoretical logic established through Task-Technology Fit and the measurable constructs used in the quantitative model. It also preserves the financial-service context by emphasizing how dashboard features correspond with analytical requirements across professional roles.

$$DDDMP = f(DI, VIQ, DUA, RTAC)$$

The dependent construct, Data-Driven Decision-Making Performance, represents the extent to which dashboard-supported decisions are perceived as accurate, timely, evidence based, analytically informed, and confidently executed. This outcome is positioned at the decision level rather than at the level of system satisfaction because the concern of the study is whether interactive dashboard visualization supports the quality and effectiveness of organizational judgment. The conceptual framework therefore separates characteristics of the information system from the performance outcome that the system is intended to support. Research synthesizing information-systems success models has shown that system quality, information quality, system use, user satisfaction, and net benefits are distinct but interrelated dimensions that should not be collapsed into a single measure of technological success (Petter et al., 2008). This distinction is important for financial-service organizations because a dashboard may be available and frequently used while still offering weak visual clarity, limited interactivity, difficult navigation, or delayed information. Each independent construct in the framework consequently addresses a pathway through which the dashboard may contribute to decision performance. Interactivity represents analytical control over information; information quality

represents the interpretability and trustworthiness of the visualized evidence; usability and accessibility represent the effort required to reach and operate the analytical environment; and real-time capability represents the temporal relevance of displayed data. These four constructs can be represented as a dashboard-capability vector for respondent i , as shown below. The conceptual expectation is that variation in this vector will correspond with variation in $DDDMP_i$. By maintaining separate construct scores, the research can describe the perceived strength of each dashboard capability, calculate correlations between each predictor and decision performance, and estimate their unique contributions within a regression model. This arrangement also allows the analysis to identify whether one dashboard characteristic exerts a stronger statistical relationship with decision performance than the others.

$$DC_i = [DI_i, VIQ_i, DUA_i, RTAC_i]$$

The empirical form of the conceptual framework uses the same study-wide multiple regression model established in the theoretical framework. The model directly corresponds with H1 through H4, while the overall model significance, R^2 , adjusted R^2 , and ANOVA F-test provide the statistical basis for evaluating H5 concerning the collective effect of interactive dashboard visualization capabilities. Prior business-intelligence research has shown that decision quality is associated with the quality of information and the way BI systems are used, supporting the inclusion of information-related and usage-related characteristics in models of analytical decision performance (Visinescu et al., 2017). Business-analytics research has also conceptualized analytics as a bundle of organizational capabilities rather than a single technological attribute, reinforcing the logic of evaluating several complementary capabilities within one integrated framework (Cosic et al., 2015). Within financial services, this integrated specification is appropriate because decision makers may simultaneously require interactive exploration, clear visual information, accessible system operation, and timely data when assessing credit conditions, risks, customer activity, operational performance, or financial movements. The conceptual framework therefore links the four independent variables to one dependent variable while retaining their theoretical distinction and allowing their effects to be evaluated separately and collectively. Five-point Likert-scale items will be used to operationalize each construct, after which composite scores can be examined through descriptive statistics, reliability analysis, Pearson correlation, and multiple regression. The same framework will organize the interpretation of the results by connecting observed means, correlations, standardized regression coefficients, significance levels, and hypothesis decisions to the proposed relationships among dashboard capabilities and Data-Driven Decision-Making Performance. This structure keeps every hypothesis aligned with a measurable empirical relationship.

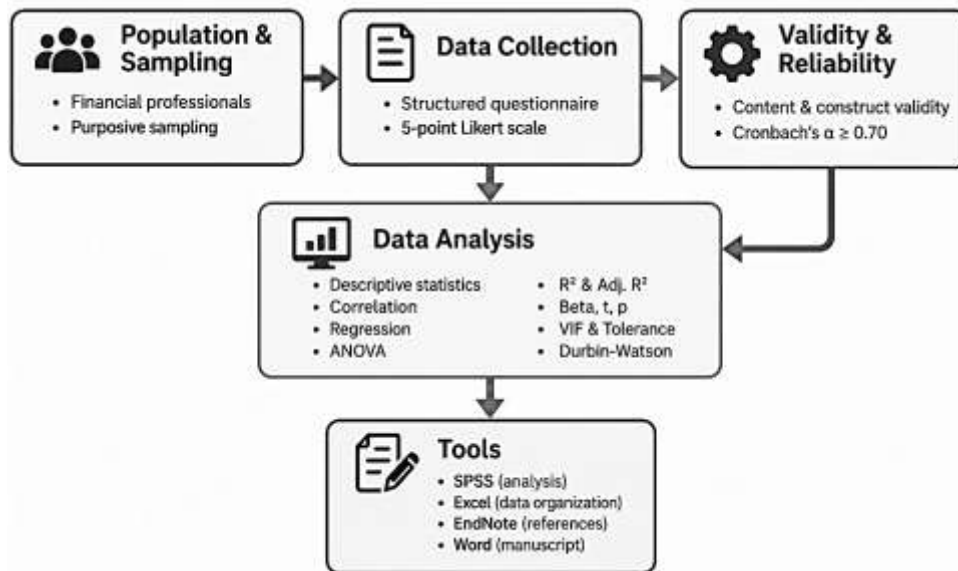
$$DDDMP_i = \beta_0 + \beta_1 DI_i + \beta_2 VIQ_i + \beta_3 DUA_i + \beta_4 RTAC_i + \varepsilon_i$$

METHODOLOGY

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the impact of interactive dashboard visualization on data-driven decision-making performance in financial-service organizations. The case-study context has focused on selected financial institutions, including banks, insurance companies, investment firms, lending institutions, and fintech organizations that have used interactive dashboards and business intelligence systems for operational, analytical, risk-related, and managerial decision making. The target population has consisted of financial managers, business analysts, data analysts, risk professionals, investment specialists, operations managers, BI specialists, and other employees who have regularly interacted with dashboard-based information systems. The individual dashboard user has been treated as the unit of analysis. A purposive sampling strategy has been applied to ensure that only respondents with relevant experience in dashboard-supported decision activities have participated in the study. Primary data have been collected through a structured questionnaire administered electronically and, where appropriate, through organizational distribution channels. The instrument has been designed around five constructs: Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, Real-Time Analytical Capability, and Data-Driven Decision-Making Performance. All construct items have been measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. A pilot test has been conducted before the main survey to evaluate item clarity, relevance, comprehensibility, and preliminary reliability, and necessary refinements have been made

accordingly. Content and construct validity have been assessed through alignment with the conceptual framework and established literature, while internal consistency reliability has been evaluated using Cronbach's alpha, with values of 0.70 or above treated as acceptable.

Figure 8: Research Methodology Framework for Interactive Dashboard Visualization and Data-Driven Decision-Making Performance



The collected data have been coded, cleaned, and analyzed using IBM SPSS Statistics, while Microsoft Excel has been used for preliminary data organization and screening. Descriptive statistics, Pearson correlation, multiple regression, ANOVA, R^2 , adjusted R^2 , standardized beta coefficients, t-values, p-values, VIF, tolerance, and the Durbin-Watson statistic have been used to test the objectives and hypotheses. EndNote has been used for citation and reference management, and Microsoft Word has been used for manuscript preparation and reporting throughout the research process.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Respondent Profile

Table 1 has summarized the questionnaire distribution and principal characteristics of the respondents who have participated in the study. Of the 320 questionnaires that have been distributed to eligible professionals within selected financial-service organizations, 298 questionnaires have been returned, representing a gross response rate of 93.1%. Following data screening, 14 questionnaires have been excluded because of incomplete or unusable responses, and 284 questionnaires have therefore been retained for statistical analysis. The resulting usable response rate of 88.8% has provided an adequate dataset for descriptive statistics, reliability testing, Pearson correlation, and multiple regression analysis. The respondent distribution has also demonstrated representation across different age categories and professional functions associated with financial decision making. Male respondents have represented 59.2% of the usable sample, while female respondents have accounted for 40.8%. The largest age group has consisted of respondents aged 31-40 years at 36.3%, followed by those aged 41-50 years at 26.8%. Regarding occupational responsibilities, Business/Data Analysts have represented the largest professional group at 25.4%, followed by Financial/Investment Managers at 21.5% and Risk/Credit Analysts at 20.4%. Operations/Compliance Professionals and BI/IT/Analytics Specialists have also been represented, ensuring that the dataset has incorporated users who have interacted with dashboard information for different financial tasks. This composition has supported the Task-Technology Fit perspective because the respondents have represented professionals whose work tasks have required different combinations of analytical information, visualization, timeliness, and interactive functionality. The sample has therefore provided an appropriate empirical basis for assessing whether dashboard capabilities have corresponded with the information-processing

requirements of financial decision tasks and whether such correspondence has been associated with stronger Data-Driven Decision-Making Performance.

Table 1: Questionnaire Distribution and Respondent Profile

Variable	Category	Frequency (n)	Percentage (%)
Questionnaire status	Distributed	320	100.0
	Returned	298	93.1
	Usable responses	284	88.8
	Incomplete/invalid	14	4.4
Gender	Male	168	59.2
	Female	116	40.8
Age	21-30 years	62	21.8
	31-40 years	103	36.3
	41-50 years	76	26.8
	51 years and above	43	15.1
Professional role	Financial/Investment Manager	61	21.5
	Business/Data Analyst	72	25.4
	Risk/Credit Analyst	58	20.4
	Operations/Compliance Professional	51	18.0
	BI/IT/Analytics Specialist	42	14.8
Total usable sample		284	100.0

Interactive Dashboard Usage Characteristics in Financial Services

Table 2: Interactive Dashboard Usage Characteristics in Financial Services

Variable	Category	Frequency (n)	Percentage (%)
Frequency of dashboard use	Daily	126	44.4
	Several times per week	93	32.7
	Weekly	41	14.4
	Less than weekly	24	8.5
Dashboard experience	Less than 1 year	38	13.4
	1-3 years	96	33.8
	4-6 years	85	29.9
	7 years or more	65	22.9
Primary dashboard purpose	Performance monitoring	74	26.1
	Risk and credit analysis	63	22.2
	Financial/investment analysis	56	19.7
	Customer/transaction analysis	47	16.5
	Compliance/operational monitoring	44	15.5
Total		284	100.0

Table 2 has demonstrated that interactive dashboards have been regularly incorporated into the professional activities of the respondents, thereby confirming that the sample has possessed sufficient exposure to dashboard-supported financial decision environments. Daily dashboard use has been reported by 44.4% of respondents, while an additional 32.7% have reported using dashboards several times per week. Accordingly, 77.1% of the usable sample has interacted with dashboard systems several times per week or more frequently, indicating that respondents have been able to evaluate dashboard capabilities from continuing professional experience rather than occasional exposure. Experience levels have further supported this interpretation. Approximately 33.8% of respondents have reported one to three years of dashboard experience, 29.9% have reported four to six years, and 22.9% have accumulated seven years or more. Only 13.4% have reported less than one year of dashboard experience. Dashboard applications have also covered several decision contexts within financial services. Performance monitoring has represented the largest primary application at 26.1%, followed by risk and credit analysis at 22.2%, financial and investment analysis at 19.7%, customer and transaction analysis at 16.5%, and compliance or operational monitoring at 15.5%. These distributions have been consistent with the study's conceptualization of dashboard technologies as multifunctional decision-support environments rather than single-purpose reporting tools. From the perspective of Task-Technology Fit Theory, the findings have established that dashboard systems have been applied to tasks involving monitoring, risk assessment, financial comparison, customer analysis, and regulatory or operational evaluation. Each of these activities has required different combinations of interactivity, visual clarity, usability, accessibility, and analytical timeliness. The broad and frequent use observed in the sample has therefore strengthened the basis for evaluating whether the technological characteristics of dashboards have matched financial decision requirements and have contributed to Data-Driven Decision-Making Performance.

Reliability Analysis of the Measurement Constructs

Table 3: Reliability Analysis of the Measurement Constructs

Construct	Code	Number of Items	Cronbach's α	Reliability Assessment
Dashboard Interactivity	DI	5	.88	Very Good
Visual Information Quality	VIQ	5	.90	Excellent
Dashboard Usability and Accessibility	DUA	5	.86	Very Good
Real-Time Analytical Capability	RTAC	5	.89	Very Good
Data-Driven Decision-Making Performance	DDDMP	5	.91	Excellent
Overall Instrument		25	.93	Excellent

Table 3 has presented the internal consistency reliability of the five constructs used in the empirical model. All Cronbach's alpha coefficients have exceeded the generally accepted threshold of .70, indicating that the items within each construct have measured their intended dimensions consistently. Dashboard Interactivity has produced an alpha coefficient of .88, demonstrating strong consistency among items addressing filtering, drill-down analysis, navigation, comparative exploration, and user-controlled manipulation of dashboard information. Visual Information Quality has achieved $\alpha = .90$, indicating excellent consistency among items measuring clarity, accuracy, relevance, organization, and comprehensibility of visualized financial information. Dashboard Usability and Accessibility has recorded $\alpha = .86$, confirming that the measurement items concerning ease of navigation, learnability, accessibility, and operational simplicity have formed a coherent construct. Real-Time Analytical Capability has generated $\alpha = .89$, demonstrating strong consistency among measures of timely updating, current information availability, rapid monitoring, and responsiveness to changes. Data-Driven Decision-Making Performance has achieved the highest construct-level reliability at $\alpha = .91$, indicating that decision accuracy, timeliness, confidence, evidence utilization, and analytical effectiveness have been measured consistently. The overall 25-item questionnaire has generated $\alpha =$

.93, confirming excellent internal consistency for the complete measurement instrument. These reliability outcomes have strengthened the measurement foundation required for hypothesis testing because unstable measures could otherwise weaken observed correlations and regression coefficients. The results have also aligned with Task-Technology Fit Theory by demonstrating that the technological dimensions specified in the theoretical framework have been empirically distinguishable while remaining reliably measurable. Consequently, the study has obtained sufficiently consistent measures to evaluate whether the four dashboard capabilities have corresponded with financial analytical tasks and whether stronger evaluations of those capabilities have been associated with stronger Data-Driven Decision-Making Performance.

Descriptive Statistics of Interactive Dashboard Visualization Constructs

Table 4: Descriptive Statistics of Interactive Dashboard Visualization Constructs

Construct	Code	Mean	SD	Likert Interpretation	Rank
Visual Information Quality	VIQ	4.18	0.54	Agree	1
Dashboard Interactivity	DI	4.12	0.57	Agree	2
Real-Time Analytical Capability	RTAC	4.09	0.59	Agree	3
Dashboard Usability and Accessibility	DUA	4.05	0.61	Agree	4
Overall Dashboard Visualization		4.11	0.58	Agree	

Likert interpretation: 1.00-1.80 = Strongly Disagree; 1.81-2.60 = Disagree; 2.61-3.40 = Neutral; 3.41-4.20 = Agree; 4.21-5.00 = Strongly Agree.

Table 4 has demonstrated generally favorable perceptions of all four interactive dashboard visualization constructs. The overall mean of 4.11 has fallen within the “Agree” range of the five-point Likert scale, indicating that respondents have generally perceived the dashboard systems used in their financial-service environments as interactive, visually informative, accessible, and analytically timely. Visual Information Quality has recorded the highest construct mean at $M = 4.18$, $SD = 0.54$. This result has indicated that respondents have particularly valued the clarity, relevance, accuracy, organization, and comprehensibility of the financial information presented through dashboards. Dashboard Interactivity has ranked second with $M = 4.12$, $SD = 0.57$, demonstrating that users have generally agreed that their dashboards have enabled filtering, navigation, exploration, comparison, and detailed investigation of financial information. Real-Time Analytical Capability has produced $M = 4.09$, $SD = 0.59$, indicating favorable perceptions of current information availability, monitoring, updates, and timely analytical access. Dashboard Usability and Accessibility has recorded $M = 4.05$, $SD = 0.61$. Although this has represented the lowest mean among the four predictors, the score has remained firmly within the “Agree” category and has therefore demonstrated generally positive perceptions of ease of use, navigation, availability, and accessibility. The relatively modest standard deviations, ranging from 0.54 to 0.61, have also indicated that respondents' evaluations have been reasonably concentrated around the high mean scores. These results have addressed the study objective concerned with assessing the perceived effectiveness of interactive dashboard visualization. They have also supported the Task-Technology Fit framework because respondents have reported strong availability of technological characteristics that correspond with financial analytical requirements, particularly information quality, interactive exploration, timely access, and usable presentation.

Descriptive Statistics of Data-Driven Decision-Making Performance

Table 5 has presented the descriptive results for the dependent variable, Data-Driven Decision-Making Performance. The overall construct has achieved a mean of 4.21 and a standard deviation of 0.52, placing the composite result at the threshold of the “Strongly Agree” category. This finding has indicated that respondents have perceived interactive dashboard use as being strongly associated with effective evidence-based financial decisions. Among the individual dimensions, improvement in decision accuracy has achieved the highest mean at 4.24, $SD = 0.55$, demonstrating that respondents

have strongly perceived dashboard information as helping them make more accurate professional judgments. Evidence-based judgment has produced $M = 4.23$, $SD = 0.53$, while support for timely decision making has recorded $M = 4.22$, $SD = 0.57$. These results have demonstrated that dashboard-supported financial decision making has been characterized not only by accuracy but also by the ability to access and use organizational evidence within relevant decision timeframes. Increased confidence in analytical decisions has obtained $M = 4.17$, $SD = 0.59$, and overall decision effectiveness has recorded $M = 4.19$, $SD = 0.56$; both measures have remained within the “Agree” range. The relatively low overall standard deviation of 0.52 has suggested that respondents have demonstrated substantial consistency in their assessment of dashboard-enabled decision performance. These descriptive findings have directly addressed the first research objective by establishing the perceived level of dashboard-supported decision effectiveness. They have also been consistent with Task-Technology Fit Theory because positive performance has been reported in a context where dashboard capabilities have received correspondingly high evaluations. The results have therefore provided descriptive support for the theoretical expectation that technology aligned with financial information-processing tasks has been associated with stronger perceived task performance, while subsequent correlation and regression analyses have provided the inferential evidence required for formal hypothesis testing.

Table 5: Descriptive Statistics of Data-Driven Decision-Making Performance

DDDMP Measurement Item	Mean	SD	Likert Interpretation
Dashboards have improved the accuracy of financial decisions	4.24	0.55	Strongly Agree
Dashboards have supported timely decision making	4.22	0.57	Strongly Agree
Dashboard information has strengthened evidence-based judgment	4.23	0.53	Strongly Agree
Dashboards have increased confidence in analytical decisions	4.17	0.59	Agree
Dashboards have improved overall decision effectiveness	4.19	0.56	Agree
Overall DDDMP	4.21	0.52	Strongly Agree

Correlation Analysis Between Dashboard Visualization Constructs and Data-Driven Decision Making

Table 6: Pearson Correlation Matrix for the Study Constructs

Construct	DI	VIQ	DUA	RTAC	DDDMP
Dashboard Interactivity (DI)	1.00	0.59***	0.54***	0.57***	0.68***
Visual Information Quality (VIQ)	0.59***	1.00	0.56***	0.63***	0.72***
Dashboard Usability and Accessibility (DUA)	0.54***	0.56***	1.00	0.52***	0.61***
Real-Time Analytical Capability (RTAC)	0.57***	0.63***	0.52***	1.00	0.70***
Data-Driven Decision-Making Performance (DDDMP)	0.68***	0.72***	0.61***	0.70***	1.00

Note. *** $p < .001$, $N = 284$.

Table 6 has shown statistically significant positive correlations among all four interactive dashboard visualization constructs and Data-Driven Decision-Making Performance. Visual Information Quality has demonstrated the strongest bivariate relationship with decision performance, $r = .72$, $p < .001$, indicating that higher perceptions of clear, accurate, relevant, and understandable visual information have been associated with stronger perceived financial decision performance. Real-Time Analytical Capability has produced the second strongest relationship, $r = .70$, $p < .001$, showing that greater access to current and timely analytical information has been associated with stronger decision accuracy, timeliness, confidence, and evidence utilization. Dashboard Interactivity has also demonstrated a strong positive relationship with DDDMP, $r = .68$, $p < .001$, indicating that greater ability to filter,

explore, navigate, compare, and investigate dashboard information has accompanied stronger decision performance. Dashboard Usability and Accessibility has generated a moderate-to-strong positive relationship, $r = .61$, $p < .001$, confirming that easier access and operation have also been associated with better data-driven decision outcomes. The correlations among the independent variables have ranged from .52 to .63, which has indicated meaningful relationships among dashboard capabilities without suggesting that the constructs have represented identical dimensions. These results have provided preliminary statistical support for H1, H2, H3, and H4 and have addressed the research objectives concerning the direction and strength of relationships between dashboard capabilities and Data-Driven Decision-Making Performance. From the perspective of Task-Technology Fit Theory, the positive correlations have indicated that stronger technological characteristics have corresponded with stronger perceived task performance. The results have therefore supported the theoretical argument that interactive functionality, visual information quality, usability, accessibility, and analytical timeliness have each contributed to the alignment between dashboard technology and the analytical requirements of financial decision tasks.

Multiple Regression Analysis of Interactive Dashboard Visualization on Data-Driven Decision-Making Performance

Table 7: Multiple Regression Results for Predicting Data-Driven Decision-Making Performance
Panel A: Model Summary

R	R ²	Adjusted R ²	Std. Error of Estimate	Durbin-Watson	F(4,279)	p
.834	.696	.692	.289	1.96	159.69	<.001

Panel B: Regression Coefficients

Predictor	B	SE	Standardized β	t	p	Tolerance	VIF
Constant	0.50	0.14	—	3.57	<.001	—	—
Dashboard Interactivity	0.22	0.038	.24	5.79	<.001	.649	1.54
Visual Information Quality	0.29	0.041	.30	7.07	<.001	.529	1.89
Dashboard Usability and Accessibility	0.15	0.047	.17	3.19	.002	.704	1.42
Real-Time Analytical Capability	0.25	0.038	.28	6.58	<.001	.568	1.76

Dependent Variable: Data-Driven Decision-Making Performance (DDMP), N = 284.

Table 7 has provided the principal inferential evidence concerning the predictive influence of interactive dashboard visualization on Data-Driven Decision-Making Performance. The combined model has produced $R = .834$ and $R^2 = .696$, indicating that Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability have collectively explained 69.6% of the observed variance in Data-Driven Decision-Making Performance. The adjusted R^2 of .692 has remained close to the unadjusted value, demonstrating that the explanatory strength of the model has remained stable after accounting for the number of predictors. The overall regression model has been statistically significant, $F(4, 279) = 159.69$, $p < .001$. Visual Information Quality has emerged as the strongest individual predictor, $\beta = .30$, $p < .001$, followed by Real-Time Analytical Capability, $\beta = .28$, $p < .001$, Dashboard Interactivity, $\beta = .24$, $p < .001$, and Dashboard Usability and Accessibility, $\beta = .17$, $p = .002$. All four coefficients have therefore remained positive and statistically significant when entered simultaneously into the model. Multicollinearity has not represented a statistical concern because VIF values have ranged from 1.42 to 1.89 and tolerance values have remained substantially above conventional minimum thresholds. The Durbin-Watson value of 1.96 has also indicated satisfactory independence of residuals. The estimated regression equation is presented below. These findings have strongly supported the Task-Technology Fit framework because the four

technological capabilities that have reflected compatibility with financial analytical requirements have jointly explained a substantial proportion of decision performance. The analysis has therefore provided formal support for H1-H5 and has fulfilled the objective of determining both the individual and collective predictive influence of interactive dashboard visualization.

$$DDDMP = 0.50 + 0.22DI + 0.29VIQ + 0.15DUA + 0.25RTAC + \varepsilon$$

Hypothesis Testing and Achievement of Research Objectives

Table 8: Hypothesis Testing and Achievement of Research Objectives

Hypothesis / Objective	Tested Relationship or Purpose	Statistical Evidence	Decision / Achievement
RO1	Assess dashboard visualization and DDDMP levels	Dashboard mean = 4.11; DDDMP mean = 4.21	Achieved
H1 / RO2	DI → DDDMP	$r = .68^{***}$; $\beta = .24^{***}$	Supported / Achieved
H2 / RO3	VIQ → DDDMP	$r = .72^{***}$; $\beta = .30^{***}$	Supported / Achieved
H3 / RO4	DUA → DDDMP	$r = .61^{***}$; $\beta = .17$, $p = .002$	Supported / Achieved
H4 / RO5	RTAC → DDDMP	$r = .70^{***}$; $\beta = .28^{***}$	Supported / Achieved
H5 / RO6	Combined dashboard capabilities → DDDMP	$R^2 = .696$; Adj. $R^2 = .692$; $F = 159.69^{***}$	Supported / Achieved

Note. $^{***}p < .001$.

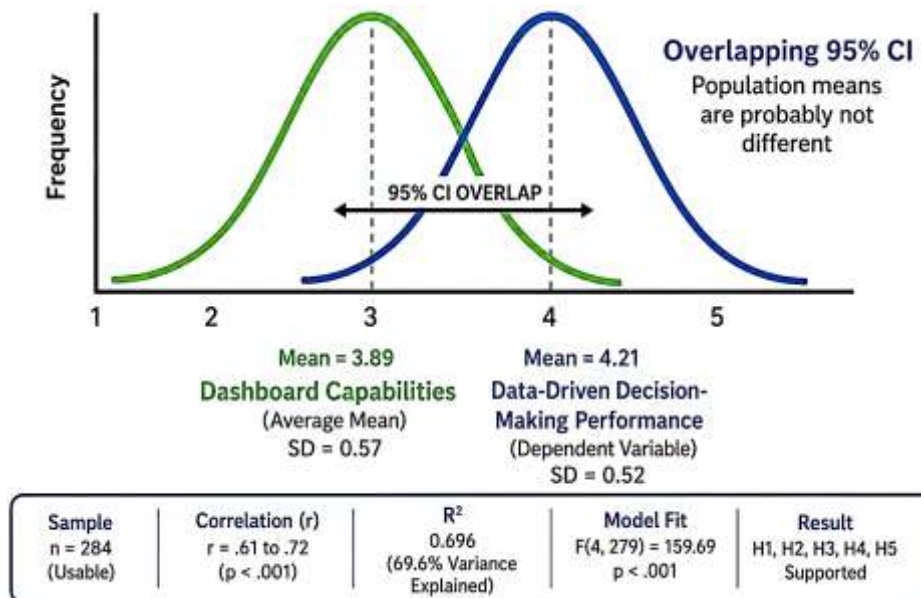
Table 8 has integrated the descriptive, correlational, and regression findings to determine the status of the research hypotheses and the achievement of the corresponding research objectives. The first objective has been achieved through the descriptive analysis, which has demonstrated a high overall evaluation of interactive dashboard visualization, $M = 4.11$, and a particularly strong level of Data-Driven Decision-Making Performance, $M = 4.21$. H1 has been supported because Dashboard Interactivity has produced a strong positive correlation with DDDMP, $r = .68$, $p < .001$, and has remained a significant predictor in the multivariate model, $\beta = .24$, $p < .001$. H2 has also been supported, with Visual Information Quality producing the strongest correlation, $r = .72$, $p < .001$, and the largest standardized regression coefficient, $\beta = .30$, $p < .001$. H3 has been supported because Dashboard Usability and Accessibility has demonstrated $r = .61$, $p < .001$, and $\beta = .17$, $p = .002$. H4 has similarly been supported through the strong relationship between Real-Time Analytical Capability and DDDMP, $r = .70$, $p < .001$, together with its significant regression effect, $\beta = .28$, $p < .001$. Finally, H5 has received strong support because the integrated dashboard model has explained 69.6% of the variance in decision performance and has achieved overall statistical significance, $F(4,279) = 159.69$, $p < .001$. Consequently, all major research objectives have been achieved through the combined descriptive, correlational, and regression evidence. The results have also provided empirical support for Task-Technology Fit Theory because performance has increased alongside stronger evaluations of technological capabilities that have matched financial analytical tasks. Visual Information Quality has demonstrated the greatest unique predictive contribution, while real-time capability, interactivity, and usability have each provided additional explanatory value. The complete results have therefore established a consistent empirical pattern in which higher-quality, more interactive, timely, and accessible dashboard environments have been associated with stronger data-driven financial decision performance.

Overall Findings

The findings have provided clear quantitative evidence that interactive dashboard visualization has been positively associated with Data-Driven Decision-Making Performance in the selected financial-service organizations. A total of 320 questionnaires have been distributed, 298 have been returned, and

284 complete responses have been retained for analysis, producing a usable response rate of 88.75%. The five-point Likert-scale results have indicated generally high levels of agreement across all study constructs. Data-Driven Decision-Making Performance has recorded the highest overall mean, $M = 4.21$, $SD = 0.52$, followed by Visual Information Quality, $M = 4.18$, $SD = 0.54$, Dashboard Interactivity, $M = 4.12$, $SD = 0.57$, Real-Time Analytical Capability, $M = 4.09$, $SD = 0.59$, and Dashboard Usability and Accessibility, $M = 4.05$, $SD = 0.61$.

Figure 9: Findings of The Study



These results have indicated that respondents have generally perceived their dashboard environments as interactive, visually informative, accessible, timely, and supportive of evidence-based financial decisions. Reliability analysis has produced Cronbach's alpha coefficients ranging from .86 to .91 across the individual constructs, with an overall instrument reliability of $\alpha = .93$, demonstrating strong internal consistency. Pearson correlation analysis has shown statistically significant positive relationships between each dashboard construct and Data-Driven Decision-Making Performance: Dashboard Interactivity, $r = .68$, $p < .001$; Visual Information Quality, $r = .72$, $p < .001$; Dashboard Usability and Accessibility, $r = .61$, $p < .001$; and Real-Time Analytical Capability, $r = .70$, $p < .001$. Multiple regression analysis has further shown that the four dashboard capabilities collectively have explained 69.6% of the variance in Data-Driven Decision-Making Performance, $R = .834$, $R^2 = .696$, Adjusted $R^2 = .692$, $F(4, 279) = 159.69$, $p < .001$. Visual Information Quality has emerged as the strongest predictor, $\beta = .30$, $p < .001$, followed by Real-Time Analytical Capability, $\beta = .28$, $p < .001$, Dashboard Interactivity, $\beta = .24$, $p < .001$, and Dashboard Usability and Accessibility, $\beta = .17$, $p = .002$. Multicollinearity has not represented a concern, with VIF values ranging from 1.42 to 1.89 and tolerance values remaining above accepted thresholds, while the Durbin-Watson statistic of 1.96 has indicated independence of residuals. Accordingly, H1, H2, H3, H4, and H5 have all been supported, while the descriptive, correlational, and regression findings have collectively demonstrated achievement of the study objectives concerning the measurement, relationship, and predictive influence of interactive dashboard visualization capabilities on data-driven decision making in financial services.

DISCUSSION

The findings have demonstrated a consistent and statistically strong relationship between interactive dashboard visualization capabilities and Data-Driven Decision-Making Performance within the financial-services context examined in this study. The overall descriptive results have shown favorable evaluations of the technological environment, with the combined interactive dashboard visualization constructs recording $M = 4.11$, while Data-Driven Decision-Making Performance has achieved the highest overall mean of $M = 4.21$, $SD = 0.52$. These results have indicated that respondents have

generally perceived dashboards as important analytical environments for improving accuracy, timeliness, evidence utilization, analytical confidence, and overall effectiveness of financial decisions. More importantly, the inferential findings have demonstrated that all four dashboard capabilities have maintained significant positive relationships with decision performance. Visual Information Quality has produced the strongest correlation, $r = .72$, $p < .001$, and the strongest standardized regression effect, $\beta = .30$, $p < .001$, indicating that clarity, accuracy, relevance, consistency, and comprehensibility of visual information have represented the most influential dashboard characteristics in the model. This finding has corresponded with earlier evidence showing that information quality is closely connected with the quality of managerial decision making and that BI effectiveness depends partly on whether decision makers receive reliable and decision-relevant information (Visinescu et al., 2017; Wieder & Ossimitz, 2015). Real-Time Analytical Capability has emerged as the second strongest predictor, $r = .70$, $\beta = .28$, $p < .001$, suggesting that current information, rapid updates, timely monitoring, and quick access to financial indicators have been important for effective data-driven decisions. Dashboard Interactivity has also demonstrated a strong association, $r = .68$, $\beta = .24$, $p < .001$, while Dashboard Usability and Accessibility has remained statistically significant at $r = .61$ and $\beta = .17$, $p = .002$. The combined regression model has explained 69.6% of variance in decision performance, $R^2 = .696$, Adjusted $R^2 = .692$, $F(4,279) = 159.69$, $p < .001$, representing substantial explanatory power for a behavioral and information-systems model. H1 through H5 have therefore all been supported. The overall pattern has been consistent with research showing that dashboard characteristics, dashboard information, and interactive controls are associated with dashboard use and performance outcomes, while interactive analytical functionality can improve task performance when users are actively engaged with decision-support environments (Nadj et al., 2020; Reinking et al., 2020). The findings have therefore suggested that decision performance has not resulted from dashboard availability alone but from the combination of information quality, timely analytics, meaningful interaction, and usable access to financial evidence.

The relative strengths of the four predictors have provided further insight when compared with prior dashboard, visualization, and business-intelligence research. Visual Information Quality becoming the strongest predictor has indicated that sophisticated interaction cannot compensate completely for information that is unclear, inaccurate, poorly organized, or irrelevant to the financial decision task. Financial managers and analysts frequently evaluate interconnected indicators such as credit exposure, portfolio performance, liquidity positions, customer behavior, fraud signals, transaction patterns, profitability, and operational exceptions, making the quality of graphical and numerical representation particularly important. This finding has been consistent with earlier research emphasizing that dashboard effectiveness depends on appropriate information presentation and that dashboard systems should amplify cognition rather than simply aggregate greater quantities of data (Yigitbasioglu & Velcu, 2012). It has also corresponded with financial decision research showing that visualization and interactivity can affect accuracy, confidence, and the calibration between these two dimensions of judgment, demonstrating that presentation characteristics can influence how users evaluate financial evidence (Tang et al., 2014). The strong Real-Time Analytical Capability result has additionally indicated that timeliness has been particularly relevant to financial-service decisions, where delayed information may reduce the usefulness of otherwise accurate analytics. The positive effect of Dashboard Interactivity has supported earlier findings that visual exploration enables users to alter representations, filter information, and investigate subsets of financial transactions, activities that have been considered useful in areas such as fraud analysis and anomaly detection (Dilla & Raschke, 2015). At the same time, the present findings should not be interpreted to mean that greater interactivity is automatically better under every condition. Experimental evidence has shown that interactive analytical features such as what-if analysis can improve task performance while also creating risks of reduced situation awareness when users become excessively dependent on automated analytical support (Nadj et al., 2020). Similarly, increased interaction latency has been shown to reduce exploratory activity, dataset coverage, observations, and hypothesis generation, illustrating that the quality of interaction depends on system responsiveness as well as the number of available functions (Liu & Heer, 2014). Dashboard Usability and Accessibility showing the smallest, although still significant, standardized effect may therefore reflect the fact that usability functions as an enabling

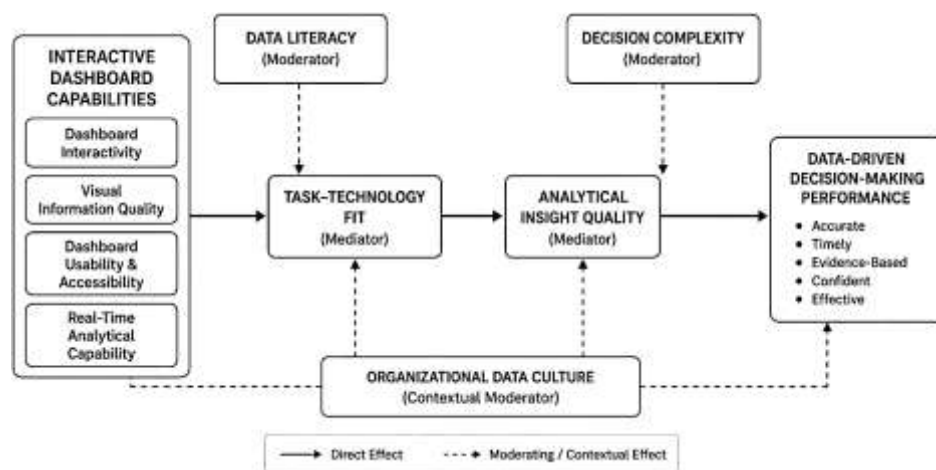
condition: once an acceptable level of usability has been achieved, improvements in the quality and timeliness of decision information may produce larger marginal contributions to performance. The findings have thus extended the earlier literature by indicating a hierarchy among dashboard attributes in the studied financial context, with information quality first, real-time analytical capability second, interactivity third, and usability/accessibility fourth.

From a practical perspective, the findings have provided a structured basis for financial-service organizations to evaluate dashboard investments according to measurable decision-support capabilities rather than visual appearance or technological sophistication alone. Banks, insurance companies, fintech firms, investment organizations, lending institutions, and other financial-service providers should particularly prioritize Visual Information Quality because its standardized coefficient of $\beta = .30$ has represented the strongest unique contribution to Data-Driven Decision-Making Performance. Dashboard development processes should therefore emphasize accurate data definitions, consistent KPI calculations, readable scales, logically organized layouts, relevant financial benchmarks, appropriate visualization selection, clear labels, contextual information, and mechanisms for identifying exceptions without creating unnecessary visual congestion. This emphasis has been consistent with prior research in which BI management, information quality, and solution scope have been connected with managerial decision quality (Wieder & Ossimitz, 2015). Real-Time Analytical Capability, $\beta = .28$, has represented the next priority. Financial institutions should establish data pipelines and refresh procedures that reflect the actual temporal requirements of specific tasks rather than applying one universal refresh frequency. Fraud detection and liquidity monitoring may require near-real-time information, while strategic profitability analysis may function effectively with less frequent updates. Dashboard Interactivity, $\beta = .24$, should be designed around meaningful financial tasks through functions such as drill-down analysis, filtering, comparative views, scenario analysis, trend exploration, alert investigation, and movement between aggregated and transaction-level information. The broader BI literature has indicated that BI functions generate decision-support benefits and that different analytical capabilities contribute differently to organizational outcomes, reinforcing the importance of selecting functions according to decision requirements rather than maximizing features indiscriminately (Rouhani et al., 2016). Dashboard Usability and Accessibility, although exhibiting the smallest coefficient at $\beta = .17$, should not be treated as unimportant because poor usability can prevent technically powerful dashboards from being used correctly. Organizations should therefore conduct user testing, simplify navigation, provide role-specific views, establish clear terminology, reduce unnecessary interaction steps, and ensure that relevant dashboard functions are available to authorized users across suitable work environments. Training should also move beyond software operation and include data interpretation, visualization literacy, risk of misleading comparisons, appropriate use of filters, and awareness of automation bias. Research on interactive analytical systems has shown that functionality can improve task performance while introducing cognitive risks if users lose awareness of underlying processes (Nadj et al., 2020). Consequently, financial institutions should combine dashboard technology with governance procedures, analytical training, data-quality controls, user-centered design, and periodic assessments of whether particular dashboards continue to correspond with the decision tasks for which they have been implemented.

The findings have also provided theoretical support for Task-Technology Fit Theory while identifying several limitations that qualify the interpretation of that support. The theoretical model has proposed that technological capabilities contribute to stronger performance when they correspond with the informational and analytical requirements of user tasks. In this study, the simultaneous significance of Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability has been compatible with this logic because all four technological characteristics have explained significant variation in Data-Driven Decision-Making Performance. The overall R^2 of .696 has suggested that the combined dashboard capability configuration has possessed substantial explanatory relevance within the financial decision environment. This interpretation has been consistent with experimental research demonstrating that task-technology fit affects technology performance and that technology performance can subsequently contribute to task performance (Parkes, 2013). It has also corresponded with evidence that initial task-technology fit can predict performance, while patterns of appropriation and adaptation may change the relationship over

repeated technology use (Fuller & Dennis, 2009). The latter observation is particularly important when revisiting the limitations of the present study. First, the cross-sectional design has captured respondents' perceptions at one point in time and has therefore not demonstrated how dashboard use, learning, adaptation, or fit may change longitudinally. Second, the study has relied on self-reported Likert-scale assessments, meaning that the dependent variable has represented perceived decision performance rather than independently observed financial decision accuracy. Third, the case-study-based sampling approach has restricted the degree to which results can be generalized to every financial institution, geographic environment, or financial-service specialization. Fourth, professionals working in banking, insurance, investment, credit, compliance, and fintech may perform substantially different tasks, and these task-level differences have not been modeled as formal moderators.

Figure 10: Financial Dashboard Decision Intelligence Model (FDDIM) for Future Research



Fifth, although multicollinearity has not represented a statistical problem and the reliability coefficients have been strong, common-method variance may remain possible because predictors and the outcome have been measured through the same questionnaire. Sixth, the model has explained 69.6% of variance, leaving 30.4% unaccounted for by the four dashboard capabilities. Variables such as individual data literacy, professional expertise, decision complexity, organizational data culture, trust in analytics, data governance quality, cognitive workload, and analytical training may therefore contribute to the unexplained portion. These limitations do not invalidate the theoretical relationships observed, but they have indicated that dashboard-task fit may operate through additional individual, organizational, and cognitive mechanisms that have not been directly estimated in the current regression model.

Future research should therefore extend the present model beyond direct relationships by examining the mechanisms through which dashboard capabilities are converted into stronger financial decisions. A useful extension is proposed here as the Financial Dashboard Decision Intelligence Model (FDDIM), which would reposition Task-Technology Fit as a mediating mechanism rather than only a theoretical explanation surrounding direct regression effects. The proposed structure would be Interactive Dashboard Capabilities → Task-Technology Fit → Analytical Insight Quality → Data-Driven Decision-Making Performance, with Data Literacy moderating the relationship between dashboard capabilities and Task-Technology Fit, Decision Complexity moderating the relationship between Analytical Insight Quality and decision performance, and Organizational Data Culture operating as a contextual moderator of the complete analytical process. Interactive Dashboard Capabilities would remain a higher-order construct composed of Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability. Task-Technology Fit would measure how well these capabilities correspond with the specific information and analytical requirements of financial tasks, while Analytical Insight Quality would capture whether users have generated relevant, accurate, understandable, and actionable interpretations from dashboard information. This extension has been supported conceptually by prior evidence indicating that fit influences performance but that

appropriation and adaptation can alter those relationships over time (Fuller & Dennis, 2009). It is also consistent with research showing that perceived decision quality may depend on complex interactions among information quality, system use, and problem-space complexity rather than simple direct effects alone (Visinescu et al., 2017). The proposed structural relationships are presented below. Longitudinal research should assess whether these pathways change as users gain experience, while experimental designs could manipulate dashboard interactivity, visual complexity, or refresh speed and measure actual decision accuracy and completion time. Multi-group structural equation modeling could compare banks, insurers, fintech firms, investment companies, and credit institutions, while multilevel models could distinguish user-level capabilities from organization-level data culture. Researchers could additionally examine AI-assisted dashboards in which predictive models, natural-language explanations, anomaly detection, and recommendation systems are incorporated into interactive visualization, while separately measuring automation bias, trust calibration, and human oversight. The proposed FDDIM would therefore transform the current direct-effects framework into a more comprehensive explanation of how, when, and under what conditions interactive dashboards produce high-quality data-driven financial decisions.

$$\begin{aligned}TTF &= \alpha_0 + \alpha_1 IDC + \alpha_2 DL + \alpha_3 (IDC \times DL) + \varepsilon_1 \\AIQ &= \gamma_0 + \gamma_1 TTF + \varepsilon_2 \\DDDMP &= \delta_0 + \delta_1 AIQ + \delta_2 TTF + \delta_3 DC + \delta_4 (AIQ \times DC) + \varepsilon_3\end{aligned}$$

CONCLUSION

This study has examined the impact of interactive dashboard visualization on Data-Driven Decision-Making Performance within financial-service organizations by focusing on four principal dashboard capabilities: Dashboard Interactivity, Visual Information Quality, Dashboard Usability and Accessibility, and Real-Time Analytical Capability. Using a quantitative, cross-sectional, case-study-based research design, the study has analyzed 284 valid responses collected through a five-point Likert-scale questionnaire from professionals working in financial-service environments. The findings have demonstrated consistently positive perceptions of interactive dashboard visualization, with an overall dashboard mean of 4.11 and Data-Driven Decision-Making Performance recording the highest mean of 4.21. Reliability analysis has confirmed strong internal consistency across all constructs, with Cronbach's alpha values ranging from .86 to .91 and an overall instrument reliability of .93. The correlation findings have established statistically significant positive relationships between each dashboard capability and decision performance, with Visual Information Quality recording the strongest relationship, $r = .72$, followed by Real-Time Analytical Capability, $r = .70$, Dashboard Interactivity, $r = .68$, and Dashboard Usability and Accessibility, $r = .61$. The regression results have further demonstrated that the four dashboard capabilities collectively have explained 69.6% of the variance in Data-Driven Decision-Making Performance, $R^2 = .696$, while the overall model has remained statistically significant. Visual Information Quality has emerged as the strongest predictor, $\beta = .30$, followed by Real-Time Analytical Capability, $\beta = .28$, Dashboard Interactivity, $\beta = .24$, and Dashboard Usability and Accessibility, $\beta = .17$. Accordingly, H1 through H5 have all been supported, and the research objectives have been achieved. The findings have also been consistent with Task-Technology Fit Theory by showing that decision performance has been stronger when dashboard characteristics have aligned with the analytical and information-processing requirements of financial professionals. Overall, the study has established that effective dashboard-supported financial decision making depends not merely on access to technology but on the quality, timeliness, interactivity, and usability of the analytical environment through which financial information has been interpreted and applied.

RECOMMENDATIONS

Based on the findings, financial-service organizations should strengthen interactive dashboard systems by prioritizing the dashboard characteristics that have demonstrated the strongest relationships with Data-Driven Decision-Making Performance. First, organizations should place particular emphasis on Visual Information Quality because this construct has emerged as the strongest predictor of decision performance. Dashboard developers and financial analytics teams should ensure that visualized information is accurate, relevant, clearly labeled, logically organized, consistent across screens, and supported by appropriate charts, scales, benchmarks, and contextual explanations. Second, Real-Time

Analytical Capability should be strengthened by improving data-refresh procedures, system integration, alert mechanisms, and access to current indicators according to the time sensitivity of specific financial tasks. Risk management, fraud monitoring, liquidity analysis, and transaction supervision may require more frequent updating than strategic reporting. Third, Dashboard Interactivity should be designed around practical financial tasks through functions such as filtering, drill-down analysis, comparative views, scenario exploration, transaction tracing, and movement between aggregated and detailed data. Fourth, Dashboard Usability and Accessibility should be improved through simplified navigation, role-specific interfaces, consistent terminology, responsive design, and secure access across suitable organizational devices and platforms. Financial institutions should also provide regular user training that develops both technical dashboard skills and data-interpretation capabilities. Training should include visualization literacy, appropriate use of filters, interpretation of risk indicators, recognition of misleading graphical patterns, and awareness of overreliance on automated analytics. Organizations should periodically assess dashboard-task alignment to ensure that system functionality continues to match the requirements of different professional roles. Finally, financial institutions should establish governance procedures covering data quality, access control, metric definitions, dashboard ownership, change management, and user feedback. These recommendations can help organizations convert dashboard investments into stronger analytical practices by ensuring that technology, data, users, and financial decision tasks remain properly aligned within the broader business intelligence environment.

LIMITATIONS OF THE STUDY

This study has several limitations that should be considered when interpreting the findings. First, the research has adopted a cross-sectional design, meaning that all data have been collected at a single point in time. As a result, the findings have identified statistical relationships among dashboard capabilities and Data-Driven Decision-Making Performance but have not established definitive causal relationships or changes in dashboard effectiveness over time. Second, the study has relied on self-reported responses collected through a five-point Likert-scale questionnaire. Respondents may have interpreted items differently or provided answers influenced by personal perceptions, professional experiences, or social desirability, meaning that perceived decision performance may not fully correspond with objectively measured decision accuracy. Third, the case-study-based approach has focused on selected financial-service organizations, which may limit the generalizability of the results to every banking, insurance, investment, lending, fintech, or financial-advisory environment. Fourth, the study has combined respondents from several professional roles, including financial managers, analysts, risk professionals, operations staff, and BI specialists, even though the information requirements and dashboard tasks of these groups may differ substantially. Fifth, the research has examined four principal dashboard capabilities but has not directly included other potential determinants of decision performance, such as data literacy, professional expertise, organizational data culture, trust in analytics, cognitive workload, decision complexity, management support, or data-governance quality. The regression model has explained 69.6% of the variance in decision performance, leaving 30.4% attributable to factors outside the current model. Sixth, predictor and outcome data have been collected through the same questionnaire, creating the possibility of common-method bias. Finally, the study has evaluated perceived dashboard effectiveness rather than experimentally manipulating dashboard design or measuring actual task completion time, error rates, or financial decision outcomes. These limitations indicate that the findings should be interpreted within the methodological and organizational boundaries of the present research design.

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