



Integrating Business Intelligence Dashboards for Real-Time Supply Chain Visibility and Operational Decision Support

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Abstract

Contemporary supply chains generate operational data, yet many organizations experience fragmented information, delayed visibility, unreliable dashboards, and slow responses because business intelligence systems are not integrated across functions and partners. This study aimed to develop and evaluate an integrated business intelligence dashboard framework for improving real-time supply-chain visibility and operational decision support. A quantitative, cross-sectional, descriptive, explanatory, and case-based research design was applied across enterprise cases in manufacturing, logistics, distribution, retail, e-commerce, warehousing, transportation, procurement, pharmaceuticals, food-related operations, and supply-chain environments. From 350 distributed questionnaires, 300 valid responses were retained, producing an effective response rate of 85.71 percent. The study examined Supply-Chain Data Integration and Quality, Real-Time Analytics and Dashboard Responsiveness, Dashboard Information Quality and Visualization Usability, System Interoperability and Technological Integration, User Analytical Competency and Organizational Readiness, Real-Time Supply-Chain Visibility, and Operational Decision Support. IBM SPSS was used for data screening, descriptive statistics, reliability testing, Pearson correlation, multiple regression, ANOVA, and diagnostic assessment. Cronbach's alpha values ranged from .823 to .917, the KMO value reached .902, and Bartlett's test was significant, $\chi^2 (861) = 5,482.76$, $p < .001$. Supply-Chain Data Integration and Quality recorded the highest predictor mean, $M = 4.13$, $SD = .54$, while Real-Time Supply-Chain Visibility and Operational Decision Support achieved $M = 4.06$, $SD = .56$ and $M = 4.09$, $SD = .55$, respectively. The visibility model explained 68.1 percent of variance, $R^2 = .681$, adjusted $R^2 = .676$, $F (5, 294) = 125.42$, $p < .001$, with data integration strongest, $\beta = .29$. The decision-support model explained 70.4 percent, $R^2 = .704$, adjusted $R^2 = .698$, $F (6, 293) = 116.15$, $p < .001$, while visibility remained strongest, $\beta = .37$. The findings imply that integrated data, responsive analytics, usable visualization, interoperable systems, and organizational readiness can strengthen monitoring, coordination, exception detection, decision speed, accuracy, and disruption response.

Keywords

Business Intelligence Dashboards; Real-Time Supply-Chain Visibility; Operational Decision Support; Supply-Chain Data Integration; Dashboard Responsiveness

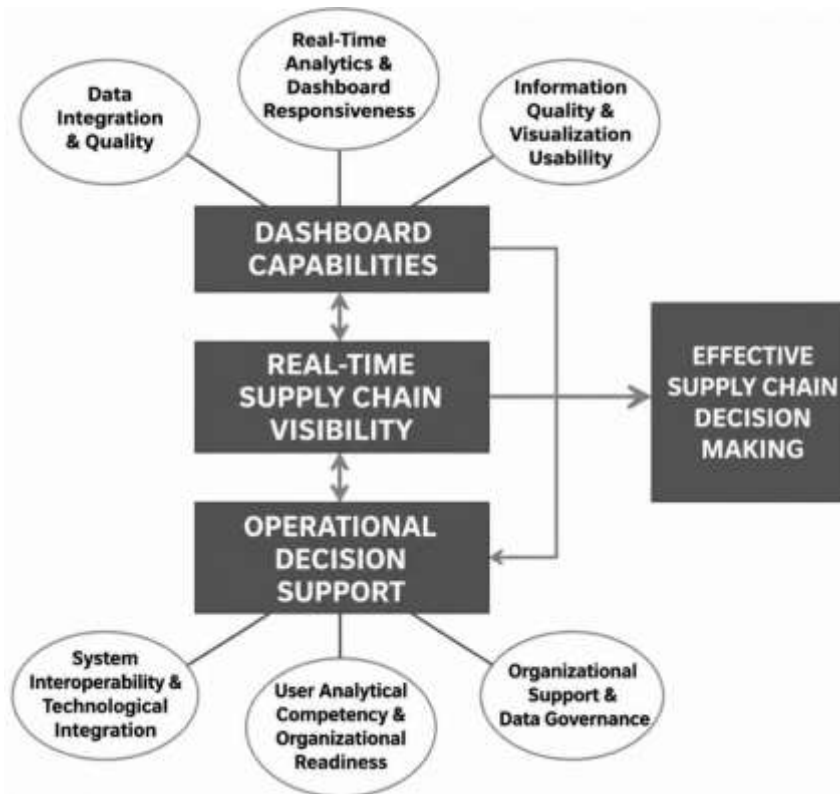
INTRODUCTION

Business intelligence refers to the integrated use of data-management technologies, analytical techniques, reporting mechanisms, and organizational processes to transform raw data into meaningful information that supports managerial understanding and decision-making. Business intelligence systems commonly combine data warehouses, data integration tools, analytical models, reporting platforms, visualization applications, and performance-monitoring mechanisms within a coordinated information environment. These systems allow organizations to collect data from multiple internal and external sources, organize them into consistent formats, identify patterns, compare actual results with predetermined targets, and distribute useful information to authorized users. Business intelligence and analytics have become central components of organizational information management because they connect extensive data resources with practical decision requirements across operational, tactical, and strategic levels (Chen et al., 2012). The business intelligence dashboard represents the visual and interactive layer of this broader architecture. A dashboard can be defined as an information interface that presents selected indicators, charts, alerts, trends, summaries, and analytical results in an organized display that enables users to monitor conditions and investigate performance variations. Dashboards are distinct from conventional static reports because users can interact with the displayed information, apply filters, compare time periods, examine underlying details, and identify unusual conditions requiring managerial attention. Dashboard effectiveness depends on the alignment of performance indicators, visual design, information content, and user decision tasks rather than on graphical appearance alone (Yigitbasioglu & Velcu, 2012). Dashboards can also function as decision-oriented services by consolidating relevant measurements and making them available to managers through accessible and regularly updated displays (Pauwels et al., 2009). Business intelligence systems generate organizational value when their information contributes to improved business-process performance and enables managers to recognize operational problems more accurately (Elbashir et al., 2008). Their success is also influenced by the interaction between technological capabilities and the characteristics of the decision environment in which information is used (Işık et al., 2013). The maturity of business intelligence systems, the quality of analytical content, and an organizational culture supportive of evidence-based decisions further determine whether available information is actively incorporated into managerial activities (Popovič et al., 2012). In international supply chains, these capabilities are especially important because procurement, production, inventory, transportation, warehousing, distribution, and customer-service activities are frequently conducted across multiple organizations, information systems, industries, and national locations.

Real-time supply-chain visibility refers to the degree to which authorized supply-chain actors can obtain timely, accurate, relevant, complete, and understandable information concerning operational events throughout the supply network. Visibility may include awareness of customer demand, supplier capacity, procurement status, raw-material availability, production progress, inventory levels, warehouse activities, order fulfilment, transportation movement, delivery performance, and emerging disruptions. Internal visibility concerns information generated within the focal organization, while external visibility involves information shared by suppliers, logistics providers, distributors, customers, and other supply-chain partners. Supply-chain visibility should not be treated as the simple existence of data or the installation of tracking technology. It is an information-processing capability through which operational data become accessible and useful to those responsible for planning, coordination, control, and response. The level of visibility achieved by an organization depends on technological resources, process structures, information-sharing routines, interorganizational relationships, and the ability to interpret exchanged information (Barratt & Oke, 2007). Supply-chain complexity and virtuality increase visibility requirements because geographically dispersed networks contain larger numbers of participants, outsourced activities, information sources, and coordination points (Caridi et al., 2010). An organization may collect substantial amounts of supply-chain data while continuing to experience low visibility when the information is delayed, fragmented, inconsistent, inaccessible, or unrelated to the decisions being performed. Visibility therefore depends on information quality and usefulness rather than data volume alone (Somapa et al., 2018). Real-time visibility can strengthen supply-chain responsiveness when shared information is supported by internal integration that allows different functions to coordinate their interpretations and actions (Williams et al., 2013).

Information sharing and connectivity also contribute to resilience and robustness by improving the capacity to identify, assess, and respond to disturbances across the supply network (Brandon-Jones et al., 2014). The conditions surrounding visibility can be organized according to antecedents, barriers, challenges, drivers, and effects, indicating that visibility emerges from an interconnected combination of technological, relational, informational, and organizational factors (Kalaiaresan et al., 2022). Inbound-logistics visibility can similarly be strengthened by mapping material and information flows, defining relevant business requirements, and selecting technologies that support the identification and management of delivery deviations (Kalaiaresan et al., 2023). Business intelligence dashboards are relevant within this environment because they can consolidate supply-chain signals into a common interface and allow users to examine relationships among supplier status, purchase orders, inventory, production, transportation events, and customer deliveries.

Figure 1: Overview of Dashboard Capabilities, Supply Chain Visibility, and Decision Support



Supply-chain data integration and quality form the informational foundation of an effective business intelligence dashboard. Supply-chain data are commonly produced by enterprise resource planning systems, warehouse-management systems, transportation-management systems, manufacturing applications, procurement platforms, supplier portals, customer databases, point-of-sale technologies, sensors, radio-frequency identification devices, spreadsheets, and third-party logistics systems. These sources may record information through different data structures, coding standards, update frequencies, definitions, ownership arrangements, and levels of detail. The resulting fragmentation can prevent managers from obtaining a unified representation of supply-chain operations even when the organization possesses advanced analytical software. Data integration refers to the process of combining information from separate systems and organizational sources into a coordinated structure that can be consistently accessed, analyzed, and interpreted. Data quality concerns the accuracy, completeness, consistency, relevance, validity, accessibility, and timeliness of the information used for analysis. Poor-quality data can produce incorrect inventory balances, misleading supplier evaluations, inaccurate delivery estimates, duplicated customer records, and unreliable performance indicators. The reliability of supply-chain analytics is therefore constrained by the quality of the underlying data used by analytical models and reporting systems (Hazen et al., 2014). Business analytics can enhance supply-

chain performance when accurate information is systematically connected with planning, sourcing, production, and delivery processes (Trkman et al., 2010). Supply-chain analytics includes descriptive, predictive, and prescriptive techniques applied to logistics and operational data at different decision levels (Wang et al., 2016). Descriptive analytics explains current and previous conditions, predictive analytics estimates probable outcomes, and prescriptive analytics assists users in evaluating possible actions. A real-time dashboard may incorporate all three forms by displaying current stock levels, estimating the probability of shortages, and identifying potential replenishment alternatives. The integration of big-data analytics with supply-chain management creates opportunities for improved coordination and monitoring, while also creating challenges associated with data access, security, quality, ownership, and interpretation (Kache & Seuring, 2017). Industrial applications of supply-chain analytics cover demand forecasting, inventory management, procurement, production planning, transportation, risk analysis, and service operations, although the level of analytical integration differs across industries and organizations (Tiwari et al., 2018). Business intelligence management quality is related to decision quality through the roles of data quality, information quality, and the functional coverage of the analytical system (Wieder & Ossimitz, 2015). Large-scale data resources create business value only when organizations establish processes for collecting, organizing, analyzing, interpreting, and applying information to operational activities (Wamba et al., 2015). Consequently, an attractive dashboard cannot provide reliable visibility when the data presented through it remain incomplete, delayed, duplicated, or inconsistent.

Real-time analytics and dashboard responsiveness describe the ability of a business intelligence environment to collect, process, analyze, and present operational information within a period suitable for the decisions being performed. Real time does not necessarily mean that every supply-chain variable must be updated continuously. It means that the delay between an operational event and its presentation is sufficiently limited to allow meaningful managerial action. Shipment locations may require frequent updates, production quantities may be refreshed by batch or shift, supplier-quality data may be updated following inspection, and sourcing indicators may be reviewed over longer periods. Dashboard responsiveness therefore involves aligning update frequency, query speed, alert delivery, and analytical processing with the time sensitivity of the relevant operational task. Supply-chain data science and predictive analytics have expanded the ability of organizations to examine complex patterns and support decisions across network design, forecasting, logistics, and risk management (Waller & Fawcett, 2013). Predictive analytics is increasingly applied to demand planning, quality management, transportation, inventory, and disruption analysis, while implementation depends on the availability of appropriate data, technological infrastructure, analytical talent, and management support (Schoenherr & Speier-Pero, 2015). Big-data analytics capability contains managerial, technological, and human dimensions, including planning, investment, coordination, connectivity, compatibility, modularity, and employee expertise (Akter et al., 2016). These capabilities are relevant to dashboard integration because a technically rapid system may provide little operational value when the displayed indicators are not connected with meaningful decision processes. Analytics capability can influence organizational performance directly and through process-oriented capabilities that allow analytical findings to be translated into changes in operational activities (Wamba et al., 2017). The assimilation of predictive analytics also depends on information sharing, technological connectivity, routinization, and senior-management commitment (Gunasekaran et al., 2017). Business intelligence and analytics contribute to performance when organizations can sense operational conditions, interpret available information, and modify processes in response to analytical findings (Torres et al., 2018). Business-process performance further connects the adoption of business analytics with organizational outcomes because analytical outputs must be incorporated into actual workflows and decisions (Aydiner et al., 2019). In a supply-chain dashboard, responsiveness may therefore be measured through update speed, analytical processing time, availability of automated alerts, accuracy of exception reports, and the ability of users to obtain detailed information without extensive delay. Information quality and visualization usability are equally important because rapid information must also be understandable, relevant, and appropriately organized for operational users.

System interoperability and technological integration represent additional requirements for creating real-time supply-chain visibility. Interoperability refers to the ability of different information systems,

applications, databases, and technological devices to exchange data and use the exchanged information without extensive manual transformation or repeated data entry. In supply-chain settings, interoperability may involve connections among business intelligence software, enterprise resource planning systems, procurement systems, manufacturing applications, warehouse-management systems, transportation-management systems, supplier platforms, customer-management systems, order-processing applications, and external logistics networks. A dashboard may contain sophisticated analytical functions while remaining disconnected from several important operational systems. In such circumstances, employees may need to transfer information manually, reconcile spreadsheets, or rely on delayed batch updates, which reduces information timeliness and increases the probability of error. Industry 4.0 has strengthened the integration of logistics activities through connected machinery, automated data capture, cyber-physical systems, decentralized communication, and the coordination of physical and digital processes (Hofmann & Rüsch, 2017). Digital supply chains use interconnected technologies and analytical systems to manage information and operational activities across organizational boundaries (Büyükoğuzkan & Göçer, 2018). Internet of Things technologies contribute to this integration by capturing data related to location, temperature, movement, equipment condition, inventory status, and product handling, thereby reducing the delay between physical events and digital reporting (Ben-Daya et al., 2019). Digital technologies also support supply-chain risk analytics by improving event identification, disruption tracking, and analysis of ripple effects across interconnected networks (Ivanov et al., 2019). Supply Chain 4.0 development includes technological instruments, managerial support, organizational capabilities, process requirements, and performance objectives, showing that integration involves more than the acquisition of digital tools (Frederico et al., 2020). Digital supply-chain twins extend this environment by creating computerized representations of network conditions based on actual information about demand, inventory, capacity, transportation, and disruptions (Ivanov & Dolgui, 2021). Such representations can provide dashboard users with a broader view of supply-chain relationships and allow them to examine the effects of operational changes across the network. Real-time monitoring systems that combine identification, sensing, communication, location, and analytical technologies have also been used to support the monitoring and control of temperature-sensitive supply chains (Mejjaoui, 2022). These technological developments demonstrate that business intelligence dashboards depend on a connected data environment through which operational events are captured, standardized, transmitted, stored, and made available for analysis. System interoperability and technological integration can therefore be measured through application compatibility, automated data exchange, cross-platform accessibility, connectivity with internal and external systems, and the consolidation of information from multiple supply-chain functions.

Human analytical competency and organizational readiness determine whether business intelligence dashboards are actively used as decision-support instruments or remain underutilized technological resources. User analytical competency includes knowledge of supply-chain processes, understanding of data definitions, ability to interpret visualizations, familiarity with performance measures, competence in using filters and drill-down functions, and confidence in evaluating alerts or predictive results. Employees may have access to accurate and timely information while remaining unable to interpret relationships among indicators or identify appropriate operational responses. Organizational readiness refers to the presence of management support, technological infrastructure, financial resources, user training, data-governance practices, cross-functional coordination, employee participation, and organizational acceptance of data-based decisions. Analytics research in operations and supply-chain management has shown that managerial processes and implementation conditions are as important as the technical features of analytical systems (Papadopoulos et al., 2017). Data resources create organizational value through knowledge-management processes and organizational agility rather than through technological ownership alone (Côrte-Real et al., 2017). Organizational Information Processing Theory provides a suitable theoretical foundation for examining these relationships because it views organizations as information-processing systems that must develop adequate capacity to address uncertainty, complexity, and interdependence. Supply chains generate high information-processing requirements because managers must coordinate activities across suppliers, production facilities, warehouses, logistics providers, distributors, and customers. Business

intelligence dashboards can increase information-processing capacity by consolidating data, reducing information-search time, displaying operational relationships, and directing attention toward exceptions. Supply-chain visibility provides access to relevant demand and supply information, analytics processes that information, and organizational flexibility enables the organization to respond to the resulting knowledge (Srinivasan & Swink, 2018). The relationship between visibility and performance is therefore influenced by the organization's ability to transform information into coordinated operational action. Big-data analytics management and employee talent capabilities have been associated with operational excellence, organizational learning, and sustainable supply-chain performance (Bag et al., 2020). Analytical and artificial-intelligence capabilities have also been related to operational performance through combinations of technological resources, managerial orientation, and organizational conditions (Dubey et al., 2020). Real-time predictive analytics can support risk identification and supply-chain agility when organizations possess the ability to interpret analytical outputs and respond to operational warnings (Aljohani, 2023). Business intelligence success is similarly influenced by the match between system capabilities and the decision environment of users (Işık et al., 2013). User analytical competency and organizational readiness should therefore be treated as core dimensions of dashboard integration rather than as secondary implementation concerns.

The central research problem arises from the frequent separation among data availability, business intelligence dashboard adoption, real-time supply-chain visibility, and operational decision support. Organizations may invest in dashboard applications while retaining fragmented databases, inconsistent information definitions, delayed refresh cycles, limited application compatibility, complicated visual interfaces, weak user training, and insufficient cross-functional coordination. Under such conditions, the dashboard may display numerous indicators without providing a reliable representation of supply-chain operations or assisting managers in selecting appropriate actions. Existing research has established that business analytics can influence supply-chain performance when analytical systems are connected with operational processes (Trkman et al., 2010). Visibility has been associated with information-sharing capabilities and organizational resources (Barratt & Oke, 2007). Supply-chain responsiveness has been linked with visibility and internal integration (Williams et al., 2013). Data quality has been identified as a major requirement for supply-chain analytics and predictive decision-making (Hazen et al., 2014). Information quality and usefulness have also been recognized as central dimensions of supply-chain visibility (Somapa et al., 2018). Analytics capability has been examined as an information-processing mechanism that complements visibility and operational flexibility (Srinivasan & Swink, 2018). The existing literature also addresses digital supply chains, predictive analytics, Internet of Things applications, Industry 4.0 technologies, digital twins, and real-time monitoring systems. A focused quantitative examination is required to determine how a combined set of dashboard-related technological, informational, human, and organizational capabilities explains real-time supply-chain visibility and operational decision support within a selected case-study environment. The purpose of this study is to examine the relationships among supply-chain data integration and quality, real-time analytics and dashboard responsiveness, dashboard information quality and visualization usability, system interoperability and technological integration, user analytical competency and organizational readiness, real-time supply-chain visibility, and operational decision support. Organizational Information Processing Theory is adopted as the main theoretical framework because the study variables represent information-processing requirements, information-processing capacity, and organizational responses to supply-chain uncertainty. The study employs a quantitative, cross-sectional, descriptive, explanatory, and case-study-based research design. Data will be collected from relevant supply-chain, logistics, operations, information-technology, and business intelligence professionals through a structured questionnaire measured with Likert's five-point scale. Descriptive statistics will determine the level of each construct, Pearson correlation analysis will assess the direction and strength of relationships, and regression modeling will estimate the individual and combined effects of the proposed predictors. The research questions examine how dashboard capabilities influence visibility, how visibility influences operational decision support, and how the proposed capabilities jointly explain variations in decision support.

Background of the Study

The increasing complexity of contemporary supply chains has created a strong need for organizations to obtain accurate, timely, and integrated information about their operational activities. Modern supply chains involve numerous interconnected processes, including procurement, supplier coordination, production planning, inventory management, warehousing, transportation, order fulfilment, distribution, and customer service (Debasish, 2021; Abdur & Iftekhar, 2021). These activities often generate large volumes of data through enterprise resource planning systems, warehouse-management systems, transportation-management systems, procurement platforms, supplier portals, customer databases, sensors, and other digital technologies (Hossan, 2021; Zahidul Begum, 2022). However, the availability of data does not automatically provide managers with a clear understanding of supply-chain conditions. In many organizations, information remains distributed across separate systems, departmental databases, spreadsheets, and external platforms, making it difficult to develop a unified view of operations (Mesbaul, 2023; Mst Shurovi, 2024). Business intelligence dashboards have emerged as important tools for addressing this information challenge by collecting, processing, organizing, and displaying operational data through interactive visual interfaces. Such dashboards can present key performance indicators, real-time alerts, inventory levels, shipment locations, supplier performance measures, production progress, order status, and exception reports in a centralized environment (Zahidul, 2024; Ali et al., 2024). Through filters, graphical summaries, comparative indicators, and drill-down functions, decision-makers can examine both overall performance and detailed operational records. The integration of business intelligence dashboards is particularly relevant to real-time supply-chain visibility because visibility requires more than access to isolated information (Arif Uz et al., 2025; Tonay et al., 2024). It requires the continuous availability of consistent and meaningful information across the entire supply network. When dashboards are properly integrated with operational systems, managers can detect stock shortages, delivery delays, supplier problems, production interruptions, transportation deviations, and changes in customer demand more quickly (Mesbaul, 2025; Mostafizur, 2025). This information can support decisions involving replenishment, resource allocation, production scheduling, order prioritization, transportation routing, and disruption management (Mostafizur et al., 2025; Syeedur & Sharmin, 2025). The usefulness of dashboards, however, depends on several connected conditions, including supply-chain data integration and quality, real-time analytical responsiveness, dashboard information quality, visualization usability, system interoperability, user analytical competency, organizational readiness, and management support. The present study is therefore grounded in the need to examine business intelligence dashboard integration as a multidimensional capability rather than a single technological application. It focuses on how this capability contributes to real-time supply-chain visibility and strengthens the operational decision-support processes of organizations operating within complex and data-intensive supply-chain environments.

Problem Statement

Organizations increasingly invest in business intelligence applications, digital supply-chain technologies, and analytical platforms, yet many continue to experience limited visibility and delayed operational decision-making. A central problem is that supply-chain data are frequently generated and stored in disconnected systems that do not communicate effectively with one another. Procurement information may be maintained in one platform, inventory records in another, transportation updates in external logistics systems, production information in manufacturing applications, and supplier data in separate databases or spreadsheets. This fragmentation can create conflicting records, duplicated information, delayed updates, incomplete performance measures, and difficulties in identifying the true condition of supply-chain operations. Even when a dashboard has been installed, it may display inaccurate, outdated, poorly integrated, or visually confusing information. As a result, managers may be unable to identify inventory shortages, supplier failures, transportation delays, production bottlenecks, order-processing problems, or unexpected disruptions at the time when corrective action is most effective. Another problem is that dashboard implementation is often treated as a technical project, while the human and organizational conditions required for effective use receive limited attention. Employees may lack sufficient analytical competency to interpret complex visualizations, understand performance indicators, evaluate predictive information, or use drill-down functions. Organizations may also provide inadequate training, limited management support, weak data-

governance procedures, and insufficient cross-functional coordination. These weaknesses can reduce user confidence in the dashboard and encourage continued dependence on manual reports, informal communication, or personal judgment. In addition, many existing studies have examined business intelligence, big-data analytics, supply-chain visibility, or operational performance as separate subjects. Fewer quantitative studies have combined technological, informational, human, and organizational dashboard capabilities within a single model that explains both real-time supply-chain visibility and operational decision support. The specific relationships among data integration and quality, real-time analytics, dashboard usability, interoperability, user competency, organizational readiness, visibility, and decision support therefore remain insufficiently clarified within case-study-based organizational settings. Without such evidence, organizations may invest in dashboard features that provide limited operational value or overlook the capabilities that most strongly affect visibility and decision quality. This study addresses the problem by statistically examining how integrated business intelligence dashboard capabilities influence real-time supply-chain visibility and how that visibility contributes to operational decision support. It uses a quantitative, cross-sectional, case-study-based design to generate empirical evidence through descriptive statistics, correlation analysis, regression modeling, and hypothesis testing.

The general objective of this study is to examine the integration of business intelligence dashboards for improving real-time supply-chain visibility and operational decision support within selected organizational case-study environments. In achieving this general objective, the study is designed to evaluate the technological, informational, human, and organizational capabilities that determine whether dashboard systems can transform fragmented operational data into timely and actionable supply-chain information. The first specific objective is to assess the existing level of supply-chain data integration and quality by examining the accuracy, completeness, consistency, relevance, accessibility, and timeliness of data collected from different operational systems. The second objective is to determine the extent to which real-time analytics and dashboard responsiveness enable managers to receive updated indicators, automated alerts, exception reports, and analytical results within the period required for operational action (Yousuf et al., 2025; Ali et al., 2025). The third objective is to evaluate dashboard information quality and visualization usability by considering the clarity, relevance, organization, graphical presentation, filtering capability, navigation, and drill-down functionality of the dashboard interface. The fourth objective is to examine the influence of system interoperability and technological integration on the effective exchange of information among enterprise resource planning, procurement, manufacturing, warehouse, transportation, supplier, and customer-related systems. The fifth objective is to assess whether user analytical competency and organizational readiness support the interpretation and application of dashboard information through employee skills, training, management commitment, technological resources, data governance, and cross-functional cooperation. The sixth objective is to measure the level of real-time supply-chain visibility across suppliers, inventory, production, warehousing, transportation, customer orders, deliveries, and operational disruptions. The seventh objective is to determine the level of operational decision support provided by business intelligence dashboards in relation to decision speed, accuracy, coordination, responsiveness, problem identification, and selection of corrective actions. The eighth objective is to examine the direction and strength of relationships among the proposed variables through Pearson correlation analysis. The ninth objective is to estimate the individual and combined effects of dashboard-related capabilities on real-time supply-chain visibility through multiple regression modeling. The tenth objective is to assess the effect of real-time visibility and dashboard capabilities on operational decision support. Through these objectives, the study seeks to test a structured model in which integrated business intelligence capabilities improve information-processing capacity, real-time visibility functions as an immediate operational outcome, and decision support represents the principal organizational result.

Research Hypotheses

The hypotheses of this study are formulated to test the proposed relationships among business intelligence dashboard capabilities, real-time supply-chain visibility, and operational decision support. The first group of hypotheses examines the factors expected to influence real-time visibility. H1 proposes that supply-chain data integration and quality have a positive and statistically significant

effect on real-time supply-chain visibility because accurate, consistent, complete, and timely data provide a reliable representation of supply-chain conditions. H2 states that real-time analytics and dashboard responsiveness have a positive and statistically significant effect on real-time supply-chain visibility by reducing the delay between operational events and managerial awareness. H3 proposes that dashboard information quality and visualization usability have a positive and statistically significant effect on real-time supply-chain visibility because clearly organized and understandable information allows users to recognize conditions and exceptions more effectively. H4 states that system interoperability and technological integration have a positive and statistically significant effect on real-time supply-chain visibility by enabling information to move across different operational applications and organizational functions. H5 proposes that user analytical competency and organizational readiness have a positive and statistically significant effect on real-time supply-chain visibility because dashboard information must be interpreted, trusted, and incorporated into routine work. The second group of hypotheses examines operational decision support. H6 proposes that supply-chain data integration and quality have a positive and statistically significant effect on operational decision support. H7 states that real-time analytics and dashboard responsiveness have a positive and statistically significant effect on operational decision support. H8 proposes that dashboard information quality and visualization usability have a positive and statistically significant effect on operational decision support. H9 states that system interoperability and technological integration have a positive and statistically significant effect on operational decision support. H10 proposes that user analytical competency and organizational readiness have a positive and statistically significant effect on operational decision support. H11 states that real-time supply-chain visibility has a positive and statistically significant effect on operational decision support because timely awareness of operational conditions enables faster and more accurate responses. H12 proposes that the combined business intelligence dashboard capabilities jointly have a positive and statistically significant effect on operational decision support. These hypotheses will be tested through correlation and regression analysis using data measured through Likert's five-point scale, with statistical significance determined according to the selected confidence level.

Significance of the Research

- i. **Theoretical significance:** The research is significant because it applies Organizational Information Processing Theory to the study of business intelligence dashboard integration in supply-chain management. It explains dashboards as mechanisms that increase organizational information-processing capacity by consolidating data, reducing information delays, improving accessibility, and supporting responses to operational uncertainty. The study also connects technological, informational, human, and organizational dimensions within a unified explanatory structure.
- ii. **Empirical significance:** The study provides quantitative evidence regarding the relationships among supply-chain data integration and quality, real-time analytics, dashboard usability, system interoperability, user competency, organizational readiness, real-time visibility, and operational decision support. Descriptive statistics, correlation analysis, regression modeling, reliability testing, and hypothesis testing will generate measurable findings concerning the strength and significance of these relationships.
- iii. **Managerial significance:** Supply-chain managers, logistics managers, procurement officers, warehouse managers, production planners, transportation coordinators, and operations managers can use the findings to identify the dashboard capabilities that require priority attention. The results can help managers determine whether operational weaknesses originate from poor data quality, slow system updates, confusing visualizations, inadequate system integration, weak analytical skills, or insufficient organizational support.
- iv. **Technological significance:** The findings can guide information-technology teams, business intelligence professionals, software developers, and system administrators in designing and integrating dashboards that reflect actual supply-chain decision requirements. The research emphasizes interoperability, automated data exchange, real-time updating, analytical responsiveness, user-friendly visualization, and access to detailed operational information.
- v. **Organizational significance:** The study highlights the importance of management commitment, employee training, data governance, cross-functional coordination, and the routine use of dashboard

information. Organizations can use the findings to strengthen analytical culture, improve confidence in operational data, reduce dependence on manual reporting, and establish clearer responsibilities for data ownership and dashboard management.

vi. **Operational significance:** The research is relevant to decisions involving inventory replenishment, production scheduling, supplier monitoring, transportation routing, warehouse coordination, order prioritization, capacity allocation, and disruption response. Improved visibility can allow organizations to identify operational problems earlier and evaluate available responses using consistent information.

vii. **Academic significance:** The study provides a structured model, clearly defined constructs, measurable variables, and testable hypotheses that may support related research in business intelligence, supply-chain analytics, information systems, logistics management, and operational decision support. It also contributes a case-study-based quantitative framework that can be replicated or adapted across industries, organizational settings, and supply-chain environments.

LITERATURE REVIEW

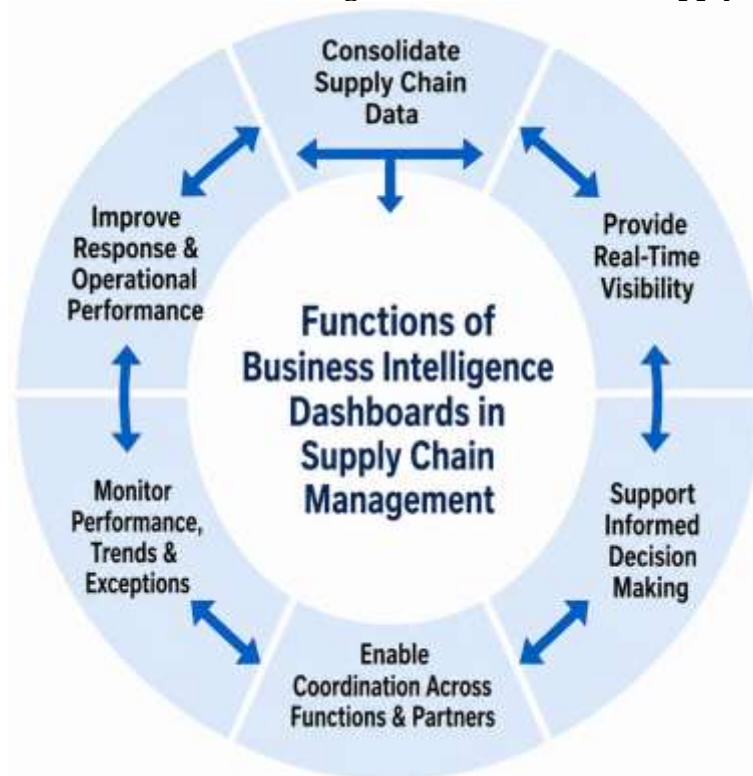
The literature concerning business intelligence dashboards, real-time supply-chain visibility, and operational decision support has developed across the interconnected fields of information systems, supply-chain management, logistics, data analytics, organizational decision-making, and digital transformation. This body of research has generally established that modern supply chains generate extensive volumes of operational information through procurement systems, enterprise resource planning platforms, warehouse-management systems, transportation-management applications, manufacturing technologies, supplier portals, customer databases, sensors, and external logistics networks. However, the availability of large quantities of data has not automatically ensured that organizations can understand current supply-chain conditions or make timely operational decisions. Scholars have therefore emphasized the importance of data integration, information quality, analytical capability, technological interoperability, visualization design, user competency, and organizational readiness in converting fragmented records into reliable managerial knowledge. Business intelligence dashboards have been examined as interactive interfaces through which organizations can consolidate key performance indicators, alerts, trends, comparisons, forecasts, and detailed operational information within a common decision environment. In supply-chain contexts, such dashboards can support the monitoring of suppliers, purchase orders, inventory, production, warehousing, transportation, customer orders, delivery performance, and disruptions. The literature has also shown that real-time visibility is not limited to tracking physical goods because it includes the timely accessibility, accuracy, relevance, completeness, and usefulness of information across internal functions and external supply-chain partners. Operational decision support has consequently been associated with the ability to identify problems, evaluate alternatives, allocate resources, coordinate responses, and implement corrective actions before operational difficulties become more severe. Organizational Information Processing Theory has provided an appropriate theoretical explanation for these relationships by suggesting that organizations must develop sufficient information-processing capacity to manage uncertainty, complexity, and interdependence. From this perspective, integrated dashboards can reduce information gaps by improving data availability, processing speed, visual interpretation, and cross-functional communication. The present literature review has therefore examined business intelligence dashboards in supply-chain management, supply-chain data integration and information quality, real-time analytics and visualization usability, real-time visibility and operational decision support, Organizational Information Processing Theory, and the conceptual relationships supporting the research hypotheses. Through these areas, the review has established the theoretical and empirical foundation required to examine how integrated dashboard capabilities have influenced visibility and decision support within the selected case-study environment.

Business Intelligence Dashboards in Supply-Chain Management

Business intelligence dashboards in supply-chain management represent the visible decision interface of a broader information architecture that collects, integrates, processes, analyzes, and communicates operational data. Their principal function is to convert dispersed records into organized displays of key performance indicators, trends, alerts, comparisons, and exceptions that managers can interpret without reviewing numerous reports or databases separately. In supply-chain settings, dashboards

may combine information concerning purchase orders, supplier performance, inventory balances, production progress, warehouse capacity, transportation status, order fulfilment, delivery reliability, and customer demand. This consolidated presentation is important because supply-chain decisions are interconnected. A late supplier shipment may alter production schedules, inventory availability, transportation requirements, and customer delivery commitments at the same time. A well-designed dashboard enables managers to observe these relationships through a common analytical environment and to move from summarized indicators to detailed records through filtering and drill-down functions. The value of the dashboard therefore depends on more than displaying data. It depends on whether the underlying business intelligence system can gather relevant information, synchronize updates, preserve consistent definitions, and present results at the speed required for operational intervention. Real-time business intelligence has been identified as particularly important for supply-chain analytics because global sourcing, product variety, service expectations, and competitive pressure require organizations to integrate information and evaluate operational conditions rapidly (Sahay & Ranjan, 2008). Dashboard effectiveness is also connected with organizational context. Strategy, structure, processes, and culture can influence both the effectiveness of business intelligence systems and the degree to which those systems contribute to organizational effectiveness (Arefin et al., 2015). Consequently, dashboards should be understood as socio-technical instruments embedded within supply-chain processes, responsibilities, and communication routines. They organize analytical information for action, but their usefulness remains dependent on data quality, system integration, user competence, management support, and the alignment of displayed measures with supply-chain objectives.

Figure 2: Core Functions of Business Intelligence Dashboards for Supply Chain Management



Within supply-chain management, the dashboard serves as a coordination mechanism linking analytical capability with operational awareness. Supply chains involve multiple functions and partners whose activities occur across locations and applications. Managers require a shared information environment that reduces delays in recognizing changes and supports consistent interpretations across procurement, production, logistics, warehousing, sales, and customer service. Business intelligence dashboards can provide this environment by presenting role-specific views of shared operational data. A procurement manager may focus on supplier lead times and purchase-order exceptions, while a warehouse manager examines space utilization, receiving delays, and picking performance. Senior managers may use integrated views showing effects on service levels, cost,

inventory exposure, and delivery reliability. Integration provides multiple useful detail levels without creating conflicting versions of operational reality. Empirical evidence has shown that supply-chain business intelligence competence can be conceptualized through managerial, technical, and cultural dimensions and that these dimensions support agile capabilities and agile performance (Sangari & Razmi, 2015). This finding is relevant because a dashboard becomes operationally valuable when technical functionality is reinforced by managerial commitment and a culture that accepts analytical information in decision processes. Logistics-based evidence also demonstrates the importance of combining business intelligence with big-data analysis rather than treating the technologies as independent activities. An integrated logistics case showed how data analysis and business intelligence could be applied across operational processes to improve productivity, delivery performance, route decisions, and the use of existing infrastructure (Jin & Kim, 2018). These observations indicate that supply-chain dashboards should not be developed as isolated visualization projects. Their design must begin with operational questions, data relationships, user responsibilities, and the decisions that follow from identified exceptions. When the dashboard architecture reflects these requirements, it can provide a consistent operational picture, support coordinated responses, and reduce dependence on manually assembled spreadsheets and delayed departmental reports.

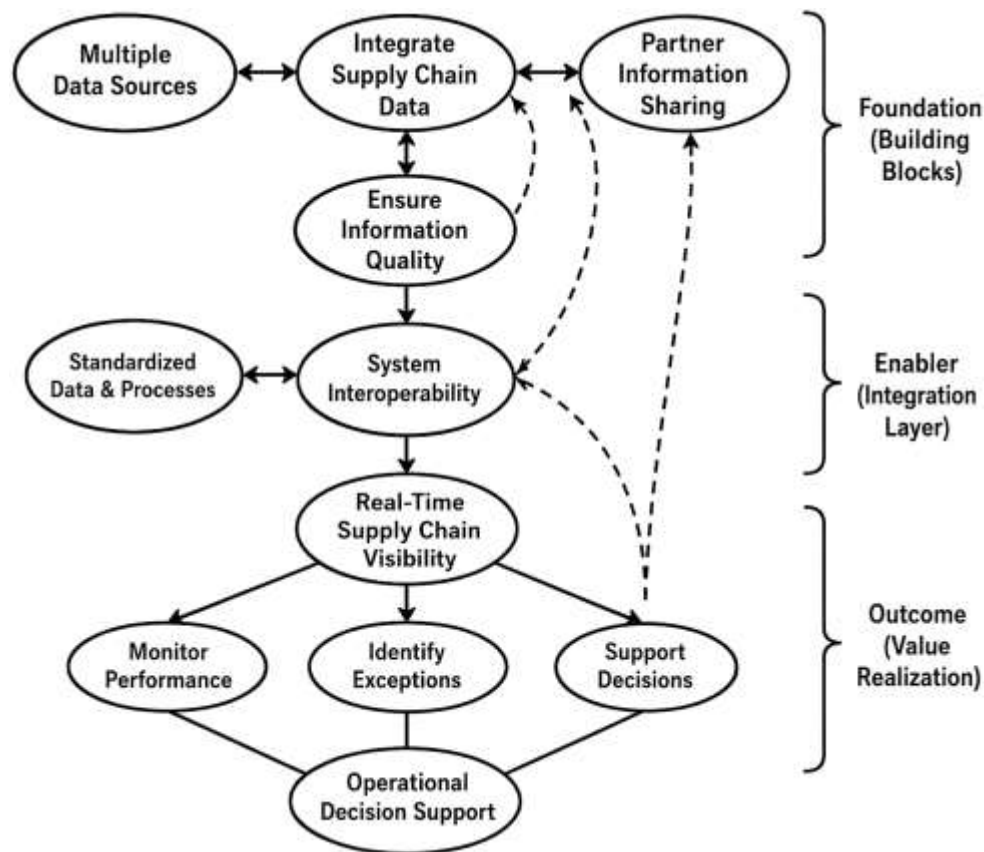
The analytical contribution of business intelligence dashboards also depends on how information is transformed into usable knowledge within supply-chain decision processes. Dashboards display descriptive measures such as inventory, order-cycle time, supplier defects, production output, transport cost, and on-time delivery. Advanced configurations may add diagnostic comparisons, predictive estimates, risk scores, scenario results, and recommended responses. These functions progress from observing conditions to explaining deviations and evaluating appropriate action. Additional complexity does not automatically improve decision support. Excessive indicators, unclear visual hierarchies, inconsistent calculations, and poorly explained model outputs can increase cognitive burden and reduce user confidence. The dashboard must balance depth with clarity, relevance, and accessibility. Users should be able to identify urgent exceptions quickly, compare current performance with targets, trace the source of a problem, and determine which operational unit is responsible for response. Evidence from logistics and supply-chain organizations indicates that analytics creates stronger value when initiatives are organized around clearly defined business problems, supported by cross-functional expertise, refined through user feedback, and embedded into the processes where decisions are made (Herden, 2020). This perspective positions the dashboard as an organizational knowledge-integration mechanism rather than a passive reporting screen. It combines data knowledge, technical knowledge, and supply-chain experience in a format intended for repeated operational use. The quality of this integration influences whether employees merely view indicators or use them to coordinate suppliers, revise production schedules, reallocate inventory, adjust transportation plans, and communicate service risks. Accordingly, business intelligence dashboards in supply-chain management should be evaluated through several connected attributes: the breadth of data integration, timeliness of updates, reliability of indicators, usability of visual presentation, availability of interactive analysis, interoperability with operational systems, and incorporation into managerial routines. These attributes establish the foundation for examining how dashboard integration contributes to real-time supply-chain visibility and operational decision support in this study.

Supply-Chain Data Integration and System Interoperability

Supply-chain data integration refers to the coordinated consolidation of operational information generated by different functions, applications, and organizational partners into a consistent environment for analysis and use. In contemporary supply chains, relevant data arise from procurement systems, enterprise resource planning platforms, manufacturing applications, warehouse systems, transportation systems, supplier portals, customer databases, sensors, and external logistics providers. These sources often apply different identifiers, formats, definitions, ownership rules, and update frequencies, creating fragmented representations of inventory, orders, production, capacity, and delivery status. Integration addresses this fragmentation by aligning data structures, synchronizing records, and enabling information to move across functional and organizational boundaries. Digitally enabled integration is valuable because information technology infrastructure can support higher-order supply-chain process capabilities rather than producing operational gains

through technology ownership alone. Integrated digital infrastructure allows firms to separate information flows from physical flows, coordinate demand planning, organize product movement, and streamline financial processes across supply-chain relationships (Rai et al., 2006). This distinction is particularly relevant to business intelligence dashboards because a dashboard cannot create reliable visibility when its underlying systems remain disconnected. A visually sophisticated display may still present incomplete or contradictory measures if inventory, procurement, production, and transportation records are collected independently. Effective integration therefore requires common data definitions, shared master records, automated exchange procedures, appropriate access controls, and clear responsibility for maintaining information. It also requires internal integration among departments before external information from suppliers and customers can be interpreted consistently. When these conditions are established, a dashboard can provide a synchronized representation of operational events and allow users to compare related indicators without manually reconciling multiple reports. Supply-chain data integration should consequently be treated as an organizational capability combining technological connectivity, standardized processes, governance arrangements, and interfunctional coordination, all of which determine whether business intelligence outputs represent the actual condition of operations in practice.

Figure 3: Integrated Framework of Data Integration, Information Quality, and System Interoperability



Information quality determines whether integrated supply-chain data can support trustworthy visibility and operational decisions. Its dimensions include accuracy, completeness, consistency, relevance, timeliness, accessibility, and detail. Accuracy concerns whether records represent events; completeness concerns whether fields and transactions are available; consistency concerns whether equivalent concepts are defined and calculated uniformly; relevance concerns whether information corresponds with the decision being performed; and timeliness concerns whether users receive it before the opportunity for intervention has passed. These dimensions are related to information sharing because supply-chain partners cannot coordinate when they exchange distorted, delayed, selective, or ambiguous data. Empirical evidence indicates that trust and a shared vision positively influence both

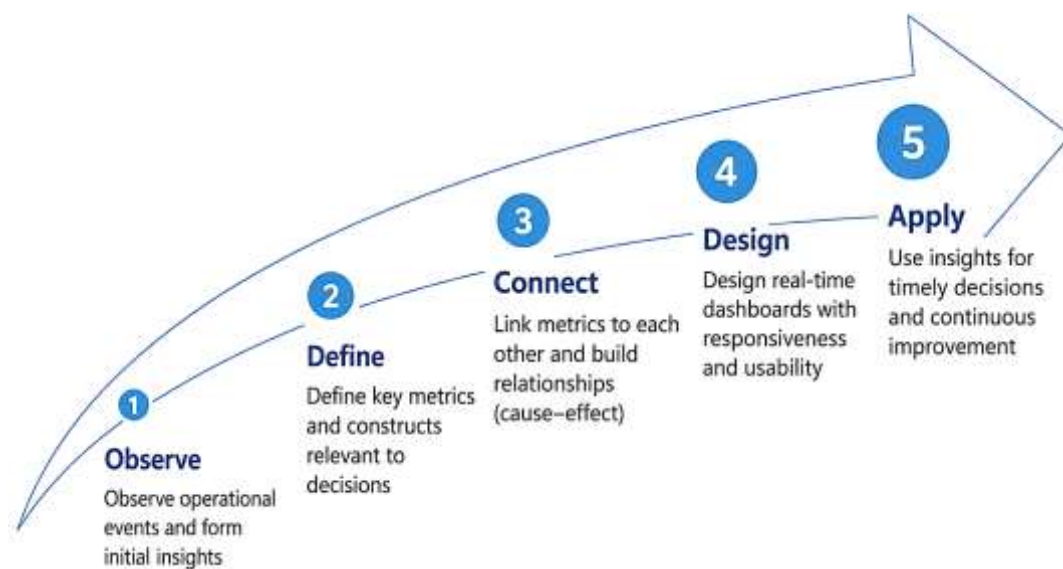
the level of information sharing and the quality of exchanged information, while supplier uncertainty can weaken these outcomes (Li & Lin, 2006). Accordingly, data quality is not solely a technical issue involving database cleansing. It also reflects relationship conditions, managerial expectations, disclosure practices, and agreement about how shared information will be used. Supply-chain practices can improve performance when information sharing is combined with planning, delivery, and coordination routines, since the value of information depends on its incorporation into operational activities (Zhou & Benton, 2007). For business intelligence dashboards, this means that indicators must be supported by transparent definitions, validated sources, consistent calculation rules, and update schedules. Users should understand where a measure originates, how frequently it is refreshed, which transactions are included, and who is responsible for correcting errors. Dashboards should also distinguish verified information from estimates and identify missing or delayed inputs that could affect interpretation. Without these controls, centralized visualization may conceal quality weaknesses by presenting uncertain data with an appearance of precision. High-quality information, in contrast, permits managers to compare suppliers, monitor stock positions, evaluate production deviations, track deliveries, and prioritize exceptions using a common evidential foundation across the supply network. System interoperability extends data integration by ensuring that technologies can exchange, interpret, and use information without manual conversion. In a supply chain, interoperability may connect enterprise, procurement, manufacturing, warehouse, transportation, supplier, and business intelligence applications. Connectivity is insufficient when systems use incompatible codes, transaction structures, product identifiers, units of measurement, or communication protocols. Semantic and process interoperability are also required so that exchanged data retain meaning and support coordinated workflows across organizations. Research on eBusiness technologies shows that technology can support customer and supplier integration, while operational benefits arise when tools strengthen production-information integration and supply-chain relationships rather than operating as isolated investments (Devaraj et al., 2007). This finding clarifies why dashboard projects should be evaluated according to the processes they connect, not merely installed software. Interoperable systems can automate the transfer of purchase orders, inventory changes, production completions, shipment events, delivery confirmations, and supplier updates into the dashboard environment. They reduce reconciliation delays and allow alerts to reflect changes across applications. Supply-chain integration includes internal, supplier, and customer dimensions, and stronger, balanced configurations of these dimensions are associated with improved operational and business performance (Flynn et al., 2010). Therefore, a business intelligence dashboard should not become another information silo positioned above disconnected systems. It should function as part of an integrated architecture through which common standards, interfaces, governance rules, and process responsibilities support reliable information movement. Interoperability also requires security controls, authorization procedures, and agreement regarding data ownership because supply-chain partners may be unwilling to expose sensitive records without safeguards. The combined quality of technological integration, information consistency, and organizational coordination determines whether dashboard users receive a continuous cross-functional view or a collection of partially connected indicators. These considerations establish data integration, information quality, and system interoperability as mutually reinforcing foundations of real-time supply-chain visibility and operational decision support.

Real-Time Analytics, Dashboard Responsiveness, and Visualization Usability

Real-time analytics in supply-chain management refers to the rapid collection, processing, analysis, and presentation of operational data within a time interval that remains useful for managerial action. The concept does not require every indicator to be refreshed continuously; instead, data latency must correspond with the urgency of the decision. Shipment locations, equipment conditions, inventory movements, production interruptions, and delivery exceptions may require immediate or frequent updates, whereas supplier scorecards and long-term capacity indicators may be refreshed less often. A responsive business intelligence dashboard therefore combines appropriate data-refresh intervals with fast query execution, automated alerts, exception identification, and access to supporting details. Real-time business intelligence also depends on a data architecture capable of capturing events, loading them into analytical repositories, monitoring processing failures, and returning information to operational applications. Evidence from the implementation of real-time business intelligence at

Continental Airlines showed that organizations must define real time according to operational needs, automate data-loading processes, establish scalable architectures, and involve users in developing applications that change daily work practices (Watson et al., 2006). These requirements apply directly to supply chains because operational events often produce connected effects across procurement, inventory, production, warehousing, transportation, and customer service. A delayed inbound shipment may alter material availability, production schedules, warehouse workload, transport planning, and delivery commitments. Dashboard responsiveness allows managers to observe such effects before they become embedded in routine reports. Its measurement should include update frequency, alert timeliness, loading reliability, query speed, and the availability of current transactional information. Responsiveness should also include the dashboard's ability to preserve consistent performance when users apply filters, open detailed views, compare locations, or investigate exceptions. A dashboard that refreshes data rapidly but responds slowly to user interaction may still delay decisions. Real-time analytics therefore requires coordinated technical performance and decision-oriented presentation during periods of elevated operational demand.

Figure 4: Process of Real-Time Analytics and Dashboard Responsiveness



Dashboard visualization usability concerns the degree to which users can understand, navigate, interrogate, and apply information presented through a visual interface. Supply-chain dashboards commonly contain charts, tables, maps, indicators, filters, alerts, and comparative measures, but these elements do not guarantee effective communication. Visualizations must correspond with the analytical purpose and the responsibilities of the intended user. Dashboards used for monitoring require prominent status indicators and exceptions, whereas analytical dashboards require comparison, filtering, linking, and drill-down capabilities. A systematic examination of dashboard practice identified differences in dashboard purposes, data semantics, visual representations, interaction levels, and contexts of use, showing that dashboards should be classified according to their design goals rather than treated as a standardized display form (Sarikaya et al., 2019). This distinction is important in supply-chain management because procurement officers, warehouse supervisors, logistics coordinators, production planners, and senior managers require different information granularity and interaction options. A uniform dashboard may create unnecessary visual density for some users while withholding essential details from others. Tailoring capabilities can address this issue by allowing dashboards to adapt content, layout, visualization, interaction, and access to the needs of particular individuals or roles. A systematic review of information dashboards found that tailoring may be implemented through customization controlled by users or personalization managed by the system, while effective solutions require careful treatment of user requirements and development resources (Vázquez-Ingelmo et al., 2019). For supply-chain dashboards, tailoring can include selecting

relevant facilities, products, suppliers, routes, time horizons, thresholds, and performance measures. Personalization should operate within governed definitions so that users do not create contradictory versions of shared indicators. Visualization usability therefore combines role relevance with organizational consistency. Clear labeling, logical reading order, limited clutter, suitable graphical encodings, understandable alerts, and contextual details allow users to recognize conditions quickly while preserving a shared interpretation of operational performance.

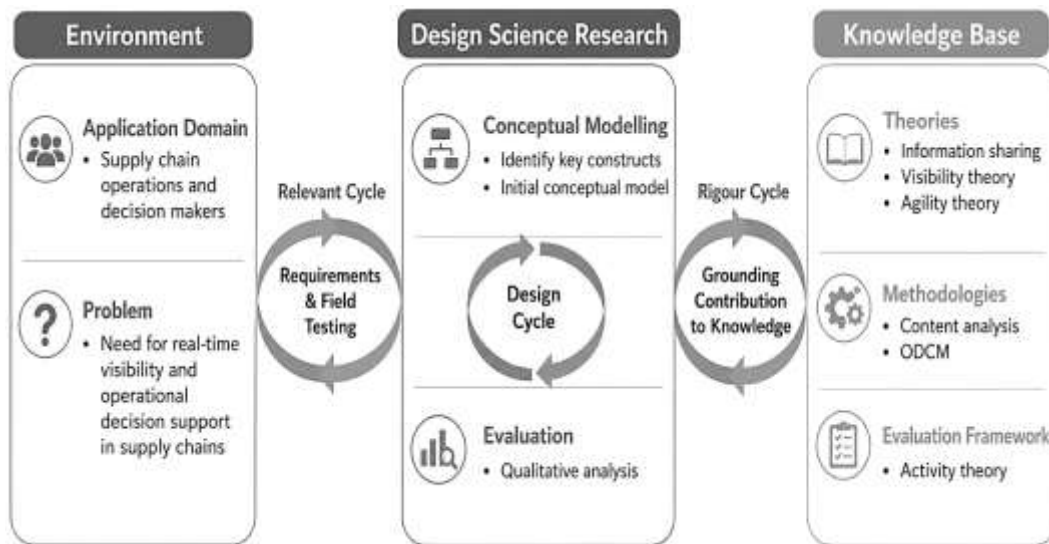
The usability of real-time analytics interfaces also depends on whether interaction design supports efficient information discovery, interpretation, and decision formation. Users must be able to locate relevant indicators, understand relationships, correct mistaken selections, and move between summary and detailed views without losing analytical context. Poorly structured interaction can increase cognitive effort, encourage inaccurate interpretation, and cause users to export data into spreadsheets or parallel reports. Empirical evaluation of interaction patterns for massive-data interfaces found that structured design patterns improved effectiveness, efficiency, and user satisfaction by supporting data discovery and visualization tasks (Iñiguez-Jarrín et al., 2020). These findings are applicable to supply-chain dashboards because operational users frequently work with large datasets containing products, orders, suppliers, locations, time periods, and event records. Interfaces should therefore provide understandable filtering, search, sorting, highlighting, zooming, and drill-down functions while showing the scope of the active analysis. Users should know which filters have been applied, when the information was refreshed, whether values are estimated, and how alerts were generated. Business intelligence visualization should also be evaluated beyond basic usability because decision experience includes interactivity, cognitive support, presentation quality, information relevance. The UXBIV framework demonstrated that business intelligence visualizations can be evaluated from users' perspectives through multiple experience dimensions and that different visualization designs can produce distinguishable decision-making experiences (Liu et al., 2023). For real-time supply-chain dashboards, this perspective means that interface quality should be assessed through both task performance and perceived usefulness. A dashboard should help users detect exceptions quickly, understand their operational significance, investigate contributing factors, and identify available responses. It should communicate urgency without excessive alarms and provide sufficient context without overwhelming the display. Dashboard responsiveness and visualization usability are therefore interdependent: rapid data processing supports timely awareness, while clear and interactive presentation enables that awareness to become informed operational judgment across supply-chain functions.

Real-Time Supply-Chain Visibility and Operational Decision Support

Real-time supply-chain visibility refers to the timely availability of accurate, relevant, and accessible information about materials, orders, inventory, production, transportation, suppliers, customers, and disruptions across interconnected supply-chain processes. It differs from simple data possession because visibility requires information to be processed, interpreted, and delivered to responsible users in a form that supports operational awareness. A firm may collect large volumes of transactional data while remaining unable to determine where a delayed order is located, whether inventory records are accurate, which supplier is responsible for a material shortage, or how a transport interruption will affect customer commitments. Effective visibility therefore combines internal information from procurement, manufacturing, warehousing, and distribution with external information received from suppliers, logistics providers, distributors, and customers. Its real-time character depends on whether information latency matches the urgency of the decision rather than whether every data element is continuously updated. Visibility becomes operationally meaningful when managers can sense emerging conditions, learn from exchanged information, coordinate interdependent activities, and integrate resources across organizational boundaries. Research has identified these sensing, learning, coordinating, and integrating dimensions as mechanisms through which visibility strengthens supply-chain reconfigurability and strategic performance (Wei & Wang, 2010). This multidimensional understanding is highly relevant to business intelligence dashboards because dashboards can organize diverse operational signals into common displays, yet their value depends on the decisions supported by those signals. Inventory availability, supplier lead time, production completion, shipment location, and delivery risk must be linked so that users can recognize how a change in one process affects

another. Real-time visibility should consequently be assessed through information timeliness, completeness, cross-functional accessibility, exception recognition, and the ability to trace summarized indicators to supporting transactions. These properties allow dashboard users to move beyond passive observation toward continuous monitoring, collaborative interpretation, evidence-based intervention, and coordinated operational control across the wider global supply network.

Figure 5: Integrated Framework for Real-Time Supply-Chain Visibility and Decision Support



Operational decision support describes the capacity of an information system to help managers recognize problems, compare alternatives, prioritize responses, allocate resources, and coordinate actions under time pressure and uncertainty. Within supply chains, these decisions include adjusting purchase orders, selecting alternative suppliers, revising production schedules, reallocating inventory, changing transport routes, prioritizing customer orders, rescheduling warehouse activities, and responding to disruptions. Visibility contributes to these decisions by reducing the informational gap between the physical condition of operations and the managerial understanding of that condition. When information sharing produces a clear view of orders, inventory, capacity, and shipment status, organizations can collaborate more effectively and respond with greater agility. Quantitative evidence indicates that information sharing positively affects supply-chain visibility and that visibility subsequently strengthens collaboration, agility, and supply-chain performance (Baah et al., 2022). Visibility therefore operates as more than a reporting outcome; it functions as an intermediate capability through which distributed information becomes coordinated action. The decision-support value of visibility also depends on speed, flexibility, leadership, and organizational willingness to act on available information. Evidence from supply-chain practitioners has shown that visibility, together with speed, flexibility, innovation, and leadership, contributes to supply-chain agility and competitive capability (Aldhaheri & Ahmad, 2023). For business intelligence dashboards, these relationships suggest that decision support should be measured through decision speed, accuracy, consistency, responsiveness, problem identification, and coordination across functions. A dashboard may display an accurate alert, but operational support remains incomplete when users cannot identify the responsible process, investigate the cause, assess possible actions, or communicate a decision to affected partners. Effective dashboards should therefore connect alerts with contextual data, historical comparisons, responsibility assignments, thresholds, and drill-down functions. Such features help users determine whether a condition represents ordinary variation or a significant exception requiring immediate intervention. Visibility supplies awareness, while decision support converts awareness into informed choice.

The relationship between real-time visibility and operational decision support becomes especially important when digital technologies generate continuous information streams that exceed unaided human processing capacity. Internet of Things devices, tracking technologies, enterprise applications,

and analytical platforms can capture product movement, storage conditions, equipment status, demand changes, and delivery progress. Business intelligence dashboards can consolidate these streams, identify exceptions, and present analytical results, but improvements depend on whether visibility connects technology with operational action. Empirical research in pharmaceutical manufacturing found positive relationships among Internet of Things capability, big-data analytics, supply-chain visibility, and operational performance, while visibility mediated the effects of digital capabilities on performance (Al-Khatib, 2023). This evidence supports the treatment of visibility as an immediate operational outcome through which integrated data and analytics influence decision effectiveness. Supply-chain control towers provide a related example because they combine centralized monitoring, analytical decision support, and process coordination. Research on intelligent dock booking demonstrated that poor coordination and disconnected updates can increase waiting time and communication effort, whereas real-time data about facility hours, dock availability, and shipment priority can support automated scheduling and efficient logistics decisions (Wyciślak & Pourhejazy, 2023). These findings clarify why dashboard responsiveness must include rapid presentation and capacity to guide action. An effective dashboard should not merely show that a shipment is late; it should help users determine the affected orders, available inventory, production consequences, alternative routes, service risks, and responsible decision owner. Real-time visibility and operational decision support are therefore connected through event capture, data integration, analytical interpretation, exception communication, alternative evaluation, and coordinated response. The study reflects this sequence by treating real-time supply-chain visibility as a principal outcome of integrated business intelligence dashboard capabilities and operational decision support as the final dependent construct. Correlation and regression analysis can determine whether stronger visibility is associated with responsive operational decisions

Theoretical Framework: Organizational Information Processing Theory

Organizational Information Processing Theory provides the principal theoretical foundation for explaining why integrated business intelligence dashboards can strengthen real-time supply-chain visibility and operational decision support. The theory views an organization as an information-processing system that must continuously acquire, interpret, distribute, and apply information to perform interdependent tasks under conditions of uncertainty. Supply chains create substantial information-processing requirements because decisions concerning suppliers, procurement, production, inventory, warehousing, transportation, orders, and customer service are distributed across multiple functions and organizational boundaries. Uncertainty increases when customer demand changes rapidly, supplier performance becomes unstable, operational data are delayed, or managers cannot identify how an event in one supply-chain process affects another. Under such conditions, the volume and complexity of the information needed to make an appropriate decision may exceed the information immediately available to organizational decision-makers. Organizational Information Processing Theory proposes that operational performance depends on achieving an appropriate fit between organizational information-processing requirements and available information-processing capacity. This theoretical relationship can be expressed in LaTeX form as follows:

$$\begin{aligned} &\text{Information-Processing Fit} \\ &= f(\text{Information-Processing Capacity}, \text{Information-Processing Requirements}) \end{aligned}$$

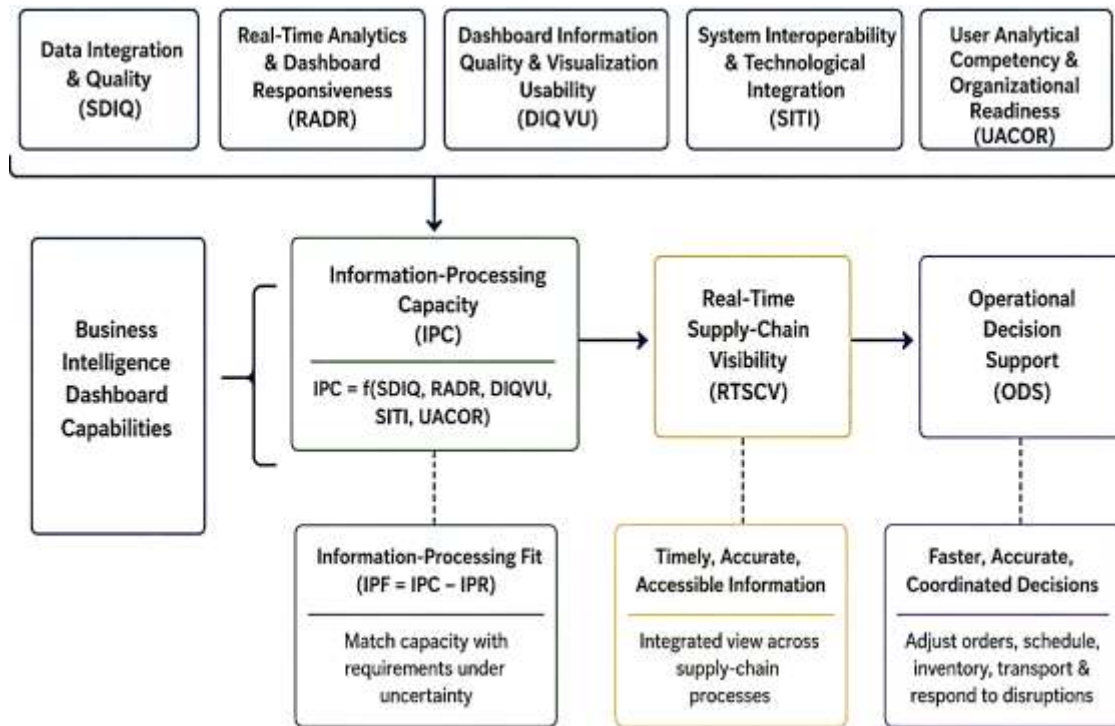
More specifically:

$$IPF = IPC - IPR$$

where *IPF* represents information-processing fit, *IPC* represents organizational information-processing capacity, and *IPR* represents information-processing requirements generated by supply-chain complexity and uncertainty. A positive or balanced information-processing fit indicates that the organization possesses sufficient capability to process the information required for its operational activities. Business intelligence dashboards can increase this processing capacity by consolidating fragmented data, standardizing performance indicators, accelerating analytical processing, visualizing operational relationships, and directing managerial attention toward important exceptions. Supply-

chain analytics capabilities applied to planning, sourcing, production, and delivery activities can improve operational transparency, although their usefulness may vary according to levels of supply uncertainty (Zhu et al., 2018). Big-data analytics capability can similarly strengthen supply-chain visibility and integration because analytical resources allow organizations to process diverse operational information and coordinate activities more effectively (Shi et al., 2023). These findings support the application of Organizational Information Processing Theory because dashboard integration represents an organizational mechanism for matching growing information requirements with stronger technological, analytical, and communicative capacity. Real-time visibility represents the immediate informational outcome of this match, while operational decision support reflects the organization's ability to transform increased awareness into timely and coordinated action.

Figure 6: Information-Processing Framework for Business Intelligence Dashboard Capabilities



Organizational Information Processing Theory also explains how the independent variables of the present study operate as complementary information-processing mechanisms rather than isolated technological characteristics. Supply-chain data integration and quality increase information-processing capacity by ensuring that records generated by procurement, production, inventory, warehousing, transportation, and external supply-chain partners are accurate, complete, consistent, timely, and accessible. Real-time analytics and dashboard responsiveness reduce temporal uncertainty by shortening the interval between the occurrence of an operational event, its analytical processing, and its presentation to responsible decision-makers. Dashboard information quality and visualization usability reduce cognitive uncertainty because clearly structured indicators, alerts, comparisons, filters, and drill-down functions allow users to recognize significant operational conditions without searching through multiple reports. System interoperability and technological integration support the automated exchange of information across applications, functions, and supply-chain organizations. User analytical competency and organizational readiness determine whether information is correctly interpreted, trusted, communicated, and incorporated into routine operational decisions. The proposed theoretical relationship among these capabilities can be presented as follows:

$$IPC = f(S, D, I, Q, RADR, DIQVU, SITI, UACOR)$$

where IPC represents information-processing capacity, $SDIQ$ represents supply-chain data integration and quality, $RADR$ represents real-time analytics and dashboard responsiveness, $DIQVU$ represents

dashboard information quality and visualization usability, *SITI* represents system interoperability and technological integration, and *UACOR* represents user analytical competency and organizational readiness. Evidence from hospital supply chains indicates that big-data analytics capability can strengthen integration and operational flexibility, particularly when analytical resources are supported by a data-driven organizational culture (Yu et al., 2020). Data analytics capability has also been found to complement organizational flexibility in strengthening supply-chain resilience, demonstrating that information-processing capacity must be accompanied by the ability to modify operations when disruptions occur (Dubey et al., 2021). These findings align with the proposed business intelligence dashboard model because visibility alone does not guarantee effective operational decision support. Managers must possess the capacity to interpret dashboard information, communicate with relevant functions, compare available alternatives, and implement an appropriate response within the available decision window. The theoretical sequence underpinning the study can therefore be expressed as follows:

BI Dashboard Capabilities → Information-Processing Capacity → Real-Time Supply-Chain Visibility
→ Operational Decision Support

This sequence illustrates that dashboard capabilities improve the quantity, quality, accessibility, speed, and interpretability of supply-chain information, while real-time visibility indicates whether these capabilities produce an integrated understanding of operational conditions.

For empirical application, Organizational Information Processing Theory is translated into a two-stage regression framework that tests whether business intelligence dashboard capabilities first increase real-time supply-chain visibility and whether those capabilities, together with visibility, strengthen operational decision support. The first multiple regression model is written in LaTeX equation format as follows:

$$RTSCV_i = \beta_0 + \beta_1 SDIQ_i + \beta_2 RADR_i + \beta_3 DIQVU_i + \beta_4 SITI_i + \beta_5 UACOR_i + \varepsilon_{1i}$$

The second regression model is expressed as:

$$ODS_i = \beta_0 + \beta_1 SDIQ_i + \beta_2 RADR_i + \beta_3 DIQVU_i + \beta_4 SITI_i + \beta_5 UACOR_i + \beta_6 RTSCV_i + \varepsilon_{2i}$$

In these equations, $RTSCV_i$ represents the real-time supply-chain visibility score for respondent i , while ODS_i represents the operational decision-support score. The term β_0 represents the regression constant or intercept. The coefficients β_1 to β_6 represent the estimated individual effects of the independent variables, while ε_{1i} and ε_{2i} represent the unexplained error terms associated with the two models. The expected directions of the regression coefficients are presented as follows:

$$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6 > 0$$

The first equation tests whether the technological, informational, human, and organizational capabilities of the dashboard jointly create sufficient information-processing capacity to improve real-time visibility. The second equation tests whether those dashboard capabilities and the visibility they generate explain decision speed, accuracy, coordination, responsiveness, and operational problem resolution. The theoretical expectation of the complete model can be summarized as:

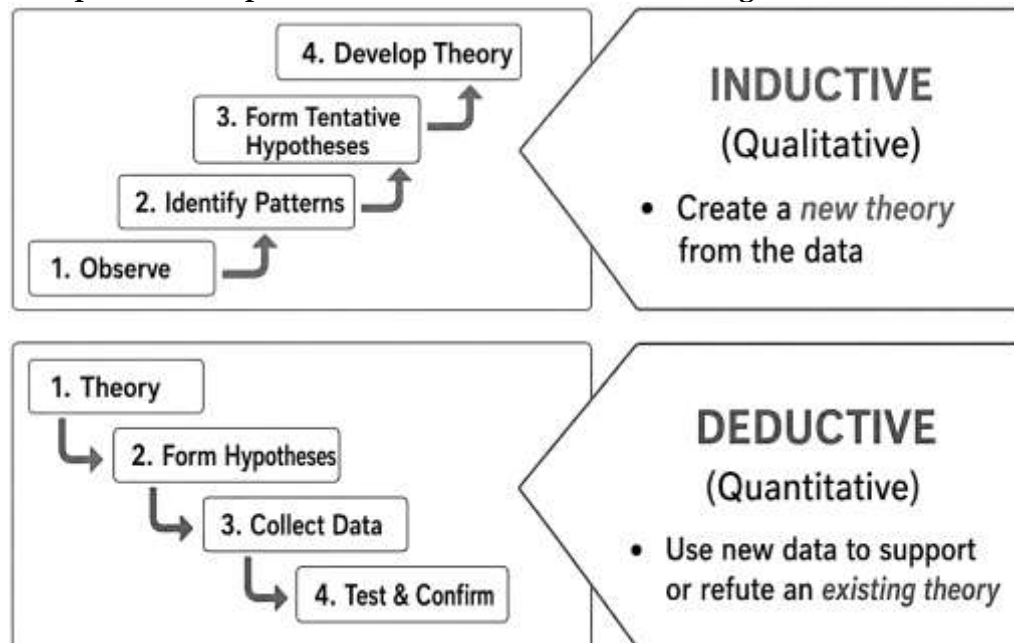
$$ODS = f(S, D, I, Q, RADR, DIQVU, SITI, UACOR, RTSCV)$$

The value of supply-chain capabilities becomes particularly important under disruption and uncertainty because organizations require greater information-processing capacity to preserve operational performance (Wong et al., 2020). Descriptive statistics will establish the perceived level of each construct, Pearson correlation analysis will measure the direction and strength of the relationships, and multiple regression modeling will estimate the unique and combined effects of the proposed predictors. Statistically significant positive coefficients will indicate that stronger dashboard capabilities are associated with greater real-time supply-chain visibility or stronger operational decision support, thereby providing measurable evidence of alignment between organizational information-processing requirements and information-processing capacity.

Conceptual Framework and Hypothesis Development

The conceptual framework of this study organizes business intelligence dashboard integration as a multidimensional capability that influences real-time supply-chain visibility and operational decision support. It links five predictor constructs: supply-chain data integration and quality, real-time analytics and dashboard responsiveness, dashboard information quality and visualization usability, system interoperability and technological integration, and user analytical competency and organizational readiness. These constructs represent the technological, informational, and organizational resources needed to convert distributed operational records into accessible knowledge. Real-time supply-chain visibility is positioned as the immediate outcome because dashboards first improve awareness of suppliers, purchases, inventory, production, warehousing, transportation, orders, deliveries, and disruptions. Operational decision support is positioned as the final outcome because improved awareness should help managers recognize problems, compare alternatives, coordinate functions, and select timely responses. The framework assumes that connectivity alone is insufficient when supply-chain members are unwilling or unable to share, interpret, and use information. Research distinguishing technological connectivity from organizational willingness shows that both dimensions are required to develop a meaningful information-sharing capability and improve operational performance (Fawcett et al., 2007).

Figure 7: Proposed Conceptual Framework for Business Intelligence Dashboard Integration



The framework consequently combines system integration with human competency, management support, data governance, and cross-functional cooperation. It also recognizes that visibility and decision support occur within collaborative relationships rather than inside one department. Supply-chain collaboration can create collaborative advantage through information sharing, synchronized decisions, incentive alignment, resource sharing, joint knowledge creation, and goal congruence, which then contributes to stronger firm performance (Cao & Zhang, 2011). Accordingly, the proposed model treats dashboard integration as an enterprise and interorganizational capability whose value depends on the coordinated operation of data, technology, people, and processes. This structure provides the basis for translating the research questions into directional hypotheses that can be assessed through Likert-scale measurements, correlation analysis, and regression modeling. It also clarifies how visibility translates integrated information into actionable operational awareness.

The first part of the conceptual framework specifies real-time supply-chain visibility as a dependent variable predicted by the five dashboard capability constructs. Supply-chain data integration and quality are expected to improve visibility because accurate, complete, consistent, timely, and accessible records allow users to observe operational conditions without reconciling conflicting sources. Real-time

analytics and dashboard responsiveness should improve visibility by reducing the delay between an event, its analysis, and its presentation. Dashboard information quality and visualization usability should strengthen visibility by making indicators relevant, understandable, navigable, and traceable to supporting transactions. System interoperability and technological integration should enhance visibility by enabling automated information exchange among enterprise, procurement, manufacturing, warehouse, transportation, supplier, and customer systems. User analytical competency and organizational readiness should strengthen visibility by ensuring that dashboard outputs are interpreted correctly, trusted, shared, and incorporated into working routines. The second part positions operational decision support as an outcome of both dashboard capabilities and real-time visibility. Business intelligence functions can generate decision-support benefits when analytical outputs improve problem identification, information evaluation, decision effectiveness, and organizational benefits, supporting the inclusion of direct capability-to-decision paths in the model (Rouhani et al., 2016). Evidence that business intelligence capabilities significantly influence dimensions of supply-chain sustainability also indicates that BI resources become valuable when they are aligned with organizational policies, managerial priorities, and operational processes (Sedigh et al., 2023). Therefore, hypotheses H1 through H5 predict positive effects of the five dashboard capabilities on real-time visibility. Hypotheses H6 through H10 predict positive effects of the same capabilities on operational decision support. H11 predicts that real-time visibility positively affects operational decision support, while H12 predicts that the dashboard capabilities jointly explain significant variation in decision support. Regression analysis will identify each construct's relative contribution after controlling for the remaining predictors. This comparison will reveal the most influential dashboard capability.

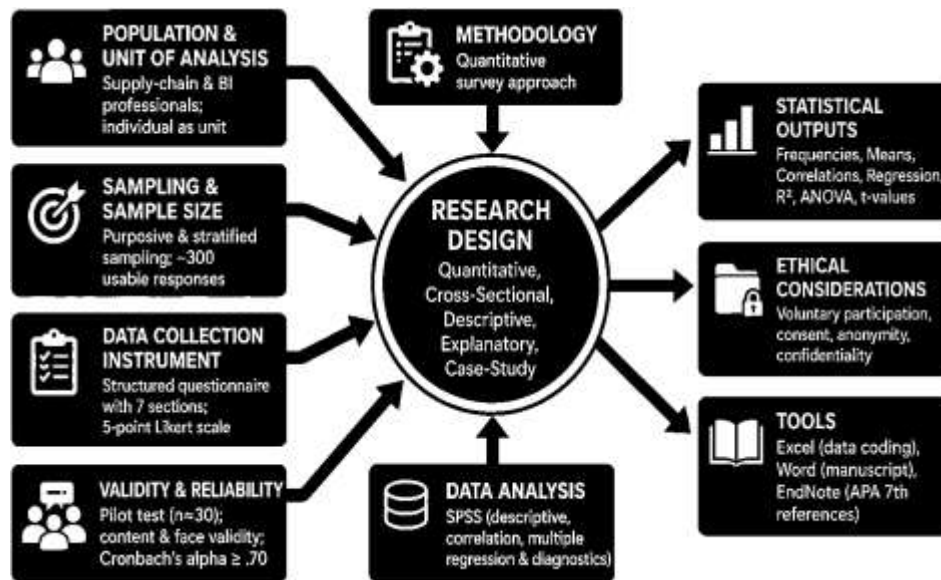
The conceptual framework is operationalized through two regression equations that correspond with the proposed causal ordering. The visibility model is expressed as $RTSCV_i = \beta_0 + \beta_1 SDIQ_i + \beta_2 RADR_i + \beta_3 DIQVU_i + \beta_4 SIT_i + \beta_5 UACOR_i + \varepsilon_{1i}$. The decision-support model is expressed as $ODS_i = \beta_0 + \beta_1 SDIQ_i + \beta_2 RADR_i + \beta_3 DIQVU_i + \beta_4 SIT_i + \beta_5 UACOR_i + \beta_6 RTSCV_i + \varepsilon_{2i}$. In these equations, RTSCV denotes real-time supply-chain visibility, ODS denotes operational decision support, SDIQ denotes supply-chain data integration and quality, RADR denotes real-time analytics and dashboard responsiveness, DIQVU denotes dashboard information quality and visualization usability, SIT denotes system interoperability and technological integration, and UACOR denotes user analytical competency and organizational readiness. The intercept is represented by β_0 , the standardized or unstandardized effects are represented by β_1 through β_6 , and the unexplained components are represented by the error terms. The expected condition is $\beta_j > 0$, indicating positive relationships between stronger dashboard capabilities, visibility, and decision support. Research showing that big-data analytics capability positively affects supply-chain performance, partly through innovation and a data-driven culture, supports modeling analytics as a bundled organizational capability rather than a standalone application (Al-Khatib & Ramayah, 2023). Composite scores will be calculated from five-point Likert items after reliability and validity assessment. Pearson correlations will establish bivariate associations, while multiple regression will estimate unique predictor effects, overall model significance, and explained variance. $R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$ will represent the proportion of outcome variation explained by each model. This framework therefore connects theory, variables, hypotheses, measurement, and statistical testing within one coherent structure designed for the selected case-study context. Adjusted R-squared will correct this estimate for model complexity, while the F statistic will determine whether the predictors jointly improve explanation beyond an intercept-only model. Standardized beta coefficients, t values, and significance levels will then support acceptance or rejection of the twelve hypotheses empirically.

METHODS

This research has adopted a quantitative, cross-sectional, descriptive, explanatory, and case-study-based design to examine the integration of business intelligence dashboards for real-time supply-chain visibility and operational decision support. The quantitative design has enabled the study to measure the proposed constructs numerically, test the research hypotheses, and determine the direction and strength of relationships among the variables. The cross-sectional approach has allowed data to be

collected from respondents during a defined period, while the case-study strategy has provided an opportunity to investigate business intelligence dashboard practices within selected organizations engaged in manufacturing, logistics, distribution, retail, e-commerce, warehousing, transportation, procurement, or related supply-chain activities.

Figure 8: Business Intelligence Dashboard Integration Framework for Supply Chain Decision Support



The study population has consisted of supply-chain managers, logistics managers, procurement officers, inventory managers, warehouse supervisors, production planners, transportation coordinators, operations managers, business intelligence analysts, data analysts, information-technology professionals, and other employees who have used or supported dashboard-based supply-chain decisions. The individual professional has served as the unit of analysis because each respondent has possessed relevant knowledge of organizational data, dashboard functionality, supply-chain visibility, or operational decision processes. A purposive and stratified sampling strategy has been used to select respondents with relevant professional experience and to secure representation from different organizational functions. Approximately 350 questionnaires have been distributed with the intention of obtaining around 300 complete and usable responses, which has been considered sufficient for descriptive analysis, correlation testing, reliability assessment, and multiple regression modeling. Data have been collected through a structured questionnaire distributed physically and electronically after organizational permission and respondent consent have been obtained. The instrument has contained a demographic section and separate measurement sections for Supply-Chain Data Integration and Quality, Real-Time Analytics and Dashboard Responsiveness, Dashboard Information Quality and Visualization Usability, System Interoperability and Technological Integration, User Analytical Competency and Organizational Readiness, Real-Time Supply-Chain Visibility, and Operational Decision Support. All construct items have been measured through Likert's five-point scale, ranging from 1 for Strongly Disagree to 5 for Strongly Agree. The questionnaire has been developed from the theoretical framework, conceptual model, research objectives, and variables identified in the literature review. A pilot test has been conducted with approximately 30 respondents who have possessed characteristics similar to those of the main study participants. Their feedback has been used to improve item clarity, wording, sequence, completion time, and relevance. Face and content validity have been assessed through review by specialists in supply-chain management, business intelligence, information systems, and research methodology. Construct validity has been evaluated through factor-related procedures, while convergent and discriminant validity have been considered where applicable. Internal consistency has been examined through Cronbach's alpha, with coefficients of .70 or above having been treated as acceptable. The collected data have been screened for missing values, outliers,

normality, linearity, homoscedasticity, independence of errors, and multicollinearity. IBM SPSS has been used to calculate frequencies, percentages, means, standard deviations, Pearson correlations, regression coefficients, R^2 , adjusted R^2 , ANOVA statistics, t-values, significance levels, tolerance values, variance inflation factors, and Durbin-Watson statistics. Microsoft Excel has been used for preliminary data organization and coding, Microsoft Word has been used for manuscript preparation, and EndNote has been used to organize references and maintain APA seventh-edition citation consistency. Ethical principles of voluntary participation, informed consent, anonymity, confidentiality, secure data management, and academic use of responses have been maintained throughout the research process.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Response Rate

Table 1: Questionnaire Distribution and Response Rate

Questionnaire status	Frequency	Percentage
Questionnaires distributed	350	100.00
Questionnaires returned	326	93.14
Questionnaires excluded	26	7.43
Valid questionnaires retained	300	85.71
Unreturned questionnaires	24	6.86

Table 1 has presented the questionnaire distribution, return, exclusion, and valid-response profile of the study. A total of 350 questionnaires have been distributed among professionals associated with supply-chain management, logistics, procurement, warehousing, production, transportation, business intelligence, data analysis, information technology, and operational decision-making. Of the distributed questionnaires, 326 have been returned, resulting in an overall return rate of 93.14 percent. This high return rate has indicated that the selected participants have shown substantial interest in business intelligence dashboard integration and have possessed sufficient familiarity with the operational issues examined by the study. Following the initial review, 26 questionnaires have been excluded because they have contained substantial missing information, uniform response patterns, internally inconsistent answers, or insufficient evidence that the respondent has regularly interacted with supply-chain information or dashboard-supported decisions. Consequently, 300 questionnaires have been retained as valid cases, producing an effective response rate of 85.71 percent. This valid sample has exceeded the minimum requirement for the proposed descriptive statistics, reliability assessment, Pearson correlation analysis, multiple regression modeling, and hypothesis testing. The retained sample has also provided an adequate ratio of cases to predictor variables because the study has included five principal dashboard capability constructs, real-time supply-chain visibility, and operational decision support. The strong effective response rate has reduced the potential influence of nonresponse error and has strengthened the stability of the calculated means, standard deviations, correlations, and regression coefficients. The response profile has supported the study objective of obtaining measurable evidence from employees who have understood supply-chain processes and business intelligence applications. From the perspective of Organizational Information Processing Theory, the number of completed responses has represented a broad organizational knowledge base drawn from employees who have experienced information-processing requirements across different operational functions. Their responses have allowed the study to assess whether the available information-processing capacity of integrated dashboards has matched the complexity and uncertainty of supply-chain activities. The valid dataset of 300 cases has therefore formed a sufficient empirical foundation for evaluating the proposed relationships among dashboard capabilities, real-time visibility, and operational decision support.

Demographic and Professional Profile of Respondents**Table 2: Demographic and Professional Profile of Respondents**

Characteristic	Category	Frequency	Percentage
Gender	Male	186	62.00
	Female	114	38.00
Age	21–30 years	78	26.00
	31–40 years	112	37.33
	41–50 years	74	24.67
	Above 50 years	36	12.00
Education	Bachelor's degree	126	42.00
	Master's degree	143	47.67
	Doctoral or professional degree	31	10.33
Professional experience	Below 5 years	58	19.33
	5–10 years	102	34.00
	11–15 years	83	27.67
	Above 15 years	57	19.00
Functional role	Supply chain and operations	72	24.00
	Logistics and transportation	58	19.33
	Procurement and inventory	54	18.00
	Warehousing and production	49	16.33
	BI, data analytics, and IT	67	22.33
Organization type	Manufacturing	92	30.67
	Logistics and distribution	69	23.00
	Retail and e-commerce	55	18.33
	Pharmaceutical and food-related	46	15.33
	Other supply-chain organizations	38	12.67
Dashboard usage	Daily	162	54.00
	Several times weekly	86	28.67
	Weekly	38	12.67
	Less frequently	14	4.67

Table 2 has demonstrated that the respondent group has contained a varied combination of demographic, educational, professional, functional, and organizational characteristics. Male respondents have represented 62.00 percent of the sample, while female respondents have represented 38.00 percent. The age distribution has shown that 37.33 percent have belonged to the 31–40-year category, followed by 26.00 percent aged 21–30 years and 24.67 percent aged 41–50 years. This distribution has indicated that most respondents have remained within professionally active age groups likely to have direct involvement in technology-enabled supply-chain operations. Regarding educational qualifications, 47.67 percent have possessed master's degrees, 42.00 percent have possessed bachelor's degrees, and 10.33 percent have held doctoral or professional qualifications. The educational profile has suggested that respondents have possessed adequate academic preparation to understand dashboard information, analytical indicators, and supply-chain decision requirements. Professional experience has also remained substantial, as 80.67 percent of the respondents have reported at least five years of work experience. The functional distribution has included employees from supply-chain and operations, logistics and transportation, procurement and inventory, warehousing and production, and business intelligence, data analytics, and information technology. This cross-functional representation has been important because integrated dashboards have connected information generated by multiple

organizational departments rather than serving one isolated function. Manufacturing organizations have accounted for the largest organizational category at 30.67 percent, while logistics and distribution organizations have accounted for 23.00 percent. The participation of retail, e-commerce, pharmaceutical, food-related, and other supply-chain organizations has increased the contextual diversity of the sample. More importantly, 54.00 percent of respondents have used dashboards daily, and an additional 28.67 percent have used them several times each week. Therefore, 82.67 percent have interacted with dashboards frequently enough to evaluate their data quality, responsiveness, usability, interoperability, and decision-support value. Organizational Information Processing Theory has emphasized that complex operations require information to be processed by individuals positioned across connected functions. The demographic and professional distribution has therefore supported the theoretical requirement for information to be assessed from different operational perspectives and has strengthened the relevance of the responses to the objectives and hypotheses of the study.

Data Screening and Statistical Assumption Testing

Table 3: Data Screening and Statistical Assumption Testing

Screening criterion	Observed result	Recommended criterion	Decision
Item-level missing data	Below 0.80%	Below 5.00%	Acceptable
Standardized extreme values	None remaining above ± 3.29	Within ± 3.29	Acceptable
Skewness	-0.74 to -0.31	Between -2 and +2	Normal
Kurtosis	-0.42 to 0.68	Between -2 and +2	Normal
Linearity	Linear patterns observed	Visible linear relationship	Satisfied
Homoscedasticity	Random residual distribution	No funnel-shaped pattern	Satisfied
Tolerance	.424 to .704	Above .10	Acceptable
Variance inflation factor	1.42 to 2.36	Below 5.00	Acceptable
Durbin-Watson, Model 1	1.91	Approximately 1.50–2.50	Independent errors
Durbin-Watson, Model 2	1.96	Approximately 1.50–2.50	Independent errors
Cook's distance	.004 to .087	Below 1.00	No influential case
Multivariate outliers	None retained at $p < .001$	No extreme retained case	Acceptable

Table 3 has summarized the procedures used to assess the completeness, distribution, and statistical suitability of the dataset before substantive analysis has been conducted. Item-level missing information has remained below 0.80 percent, which has fallen considerably below the commonly accepted threshold of 5 percent. The small number of missing observations has been handled through appropriate case-level and item-level screening before composite construct scores have been calculated. Questionnaires containing extensive missing responses or unusable patterns have already been removed during the response validation process. Standardized scores have shown that no extreme univariate observations have remained beyond ± 3.29 in the final dataset. Skewness values have ranged from -0.74 to -0.31, while kurtosis values have ranged from -0.42 to 0.68. These results have remained within accepted boundaries and have indicated that the measured constructs have approximated normal distributions. Scatterplots involving each predictor and outcome have displayed generally linear patterns, while plots of standardized residuals against predicted values have shown random distributions without pronounced funnel shapes. The assumptions of linearity and homoscedasticity have therefore been satisfied. Multicollinearity has also been examined because the dashboard capability variables have represented related dimensions of a broader information-processing system. Tolerance values have ranged from .424 to .704, and variance inflation factor values have ranged from

1.42 to 2.36. These values have remained within acceptable limits and have indicated that the predictors have shared meaningful relationships without becoming statistically redundant. The Durbin–Watson values of 1.91 for the real-time visibility model and 1.96 for the operational decision-support model have demonstrated acceptable independence of errors. Cook’s distance values have remained substantially below 1.00, and no retained multivariate observation has exceeded the conservative probability criterion. These findings have confirmed that the regression coefficients have not been controlled by a small number of influential cases. Organizational Information Processing Theory has treated data accuracy and interpretability as essential components of information-processing capacity. The successful completion of the screening procedures has therefore ensured that the statistical information used to evaluate theoretical fit has remained sufficiently accurate, stable, and interpretable. The results have supported the use of Pearson correlation analysis and multiple regression modeling for testing the study objectives and hypotheses.

Reliability and Validity Analysis

Table 4: Reliability and Validity Results for the Study Constructs

Construct	Items	Cronbach’s alpha	Composite reliability	AVE	Loading range	Decision
Supply-Chain Data Integration and Quality	6	.917	.929	.687	.74–.88	Reliable and valid
Real-Time Analytics and Dashboard Responsiveness	6	.901	.918	.653	.72–.86	Reliable and valid
Dashboard Information Quality and Visualization Usability	6	.889	.909	.626	.70–.84	Reliable and valid
System Interoperability and Technological Integration	6	.872	.899	.599	.68–.82	Reliable and valid
User Analytical Competency and Organizational Readiness	6	.823	.868	.524	.64–.79	Reliable and valid
Real-Time Supply-Chain Visibility	6	.908	.925	.674	.73–.87	Reliable and valid
Operational Decision Support	6	.914	.930	.690	.74–.88	Reliable and valid
Overall KMO	42	.902				Excellent adequacy
Bartlett’s test	42	$\chi^2(861) = 5,482.76$			$p < .001$	Significant

Table 4 has presented the reliability and validity results for the seven constructs measured through 42 questionnaire items. Cronbach’s alpha values have ranged from .823 to .917, and every coefficient has exceeded the minimum acceptable value of .70. Supply-Chain Data Integration and Quality has recorded the highest alpha coefficient of .917, indicating that its six measurement items have consistently assessed the quality, accessibility, synchronization, and integration of operational data. Operational Decision Support has recorded an alpha of .914, while Real-Time Supply-Chain Visibility has achieved .908. These values have confirmed that the outcome variables have been measured with strong internal consistency. User Analytical Competency and Organizational Readiness has produced the lowest alpha value of .823, although this coefficient has still demonstrated good reliability. Composite reliability values have ranged from .868 to .930 and have provided additional evidence that the indicator groups have consistently represented their respective constructs. Average variance extracted values have ranged from .524 to .690, with every value exceeding the required threshold of .50. Therefore, the constructs have explained more than half of the variance in their associated measurement items, supporting convergent validity. Standardized factor loadings have ranged from .64 to .88, and no retained item has fallen below the acceptable loading boundary. The Kaiser–Meyer–Olkin measure has reached .902, indicating excellent sampling adequacy for factor-related assessment.

Bartlett's Test of Sphericity has been statistically significant, $\chi^2(861) = 5,482.76$, $p < .001$, demonstrating that the correlations among the 42 measurement items have been sufficient for construct validation. Discriminant validity has also been supported because the square roots of the average variance extracted values have exceeded the strongest correlations involving their respective constructs. These findings have demonstrated that the measurement model has distinguished data integration, analytics responsiveness, dashboard usability, interoperability, human readiness, visibility, and decision support while recognizing their theoretical relationships. Organizational Information Processing Theory has required reliable measures of both information-processing capacity and information-processing outcomes. The reliability and validity evidence has confirmed that the five dashboard capability constructs have represented distinct dimensions of information-processing capacity, while visibility and decision support have represented measurable organizational outcomes. The measurement results have therefore supported the subsequent testing of H1 through H12.

Descriptive Statistics of Supply-Chain Data Integration and Quality

Table 5: Descriptive Statistics of Supply-Chain Data Integration and Quality

Measurement item	Mean	SD	Rank	Interpretation
Dashboard data have been accurate and dependable	4.22	.51	1	Very high
Data from major supply-chain functions have been integrated	4.18	.53	2	High
Operational records have been updated consistently	4.15	.55	3	High
Common data definitions have been used across functions	4.12	.56	4	High
Required information has been complete and accessible	4.08	.58	5	High
Duplicate and contradictory records have been minimized	4.03	.61	6	High
Overall construct	4.13	.54		High

Table 5 has shown that Supply-Chain Data Integration and Quality has received an overall mean of 4.13 and a standard deviation of .54, indicating a high level of positive agreement among the respondents. The highest-rated item has concerned the accuracy and dependability of dashboard data, with a mean of 4.22. Under the adopted Likert interpretation, this item has reached the very-high category and has suggested that most respondents have considered the dashboard information sufficiently reliable for monitoring supply-chain operations. The integration of data from major supply-chain functions has obtained the second-highest mean of 4.18, showing that procurement, inventory, production, warehousing, transportation, and order-related information has generally been brought together within the business intelligence environment. Consistent updating of operational records has achieved a mean of 4.15, while the use of common data definitions has recorded 4.12. These results have indicated that organizations have established reasonably standardized processes for updating and interpreting dashboard measures. Completeness and accessibility have received a mean of 4.08, demonstrating that users have generally obtained the information required for their responsibilities. The lowest item, although still highly rated, has involved the minimization of duplicated and contradictory records, with a mean of 4.03. This relative weakness has suggested that some organizations have continued to experience data reconciliation problems across separate applications or departments. The overall result has addressed the study objective of assessing the level of supply-chain data integration and quality. It has also provided descriptive support for H1 and H6, which have proposed positive effects of this construct on real-time supply-chain visibility and operational decision support. Organizational Information Processing Theory has indicated that organizations must possess accurate, relevant, and coordinated information to match the information-processing requirements created by uncertainty and interdependence. The high mean has therefore suggested that the participating organizations have developed strong foundational information-processing capacity. The lower score for duplicate and contradictory records has also shown that the theoretical fit has not been perfect, since inconsistent source systems can increase processing requirements and delay managerial interpretation. Overall, the construct has emerged as the highest-rated dashboard capability and has provided the strongest descriptive foundation for the subsequent correlation and regression findings.

Descriptive Statistics of Real-Time Analytics and Dashboard Responsiveness**Table 6: Descriptive Statistics of Real-Time Analytics and Dashboard Responsiveness**

Measurement item	Mean	SD	Rank	Interpretation
Dashboards have updated critical operational indicators promptly	4.16	.54	1	High
Automated alerts have identified important exceptions quickly	4.12	.56	2	High
Users have obtained analytical results without excessive delay	4.09	.57	3	High
Dashboard queries and filters have responded efficiently	4.06	.59	4	High
Real-time trends have supported rapid operational monitoring	4.02	.61	5	High
Predictive warnings have been available for emerging problems	3.97	.65	6	High
Overall construct	4.07	.57		High

Table 6 has demonstrated that Real-Time Analytics and Dashboard Responsiveness has achieved an overall mean of 4.07 and a standard deviation of .57. This result has indicated that respondents have generally agreed that the business intelligence dashboards have processed and presented supply-chain information within useful operational timeframes. Prompt updating of critical indicators has received the highest item mean of 4.16, suggesting that inventory changes, shipment events, production conditions, order status, and other important measures have been refreshed sufficiently rapidly for monitoring purposes. Automated exception alerts have achieved a mean of 4.12, showing that dashboard systems have helped users identify deviations without examining every transaction manually. The availability of analytical results without excessive delay has recorded 4.09, while the efficiency of dashboard queries and filters has received 4.06. These findings have indicated that both background data processing and direct user interaction have generally remained responsive. Real-time trend monitoring has obtained a mean of 4.02, demonstrating that users have been able to observe changes in performance over short operational periods. Predictive warnings have received the lowest mean of 3.97. Although this value has remained within the high category, it has suggested that predictive functions have been less fully developed than descriptive monitoring and automated exception reporting. The overall result has addressed the objective of determining whether dashboards have supplied analytical information at the speed required for operational action. It has provided descriptive support for H2 and H7, which have proposed that real-time analytics and dashboard responsiveness positively influence visibility and decision support. Organizational Information Processing Theory has emphasized the importance of matching the speed of information processing with the rate at which uncertainty develops. A delayed dashboard can leave the organization with insufficient processing capacity even when the underlying information has been accurate. The high construct mean has shown that the participating organizations have generally reduced this temporal gap. The lower predictive-warning mean has indicated that the present systems have remained stronger at reporting current conditions than anticipating emerging disruptions. Thus, the dashboards have increased immediate processing capacity, while more advanced predictive capabilities have remained an area requiring further development.

Descriptive Statistics of Dashboard Information Quality and Visualization Usability**Table 7: Descriptive Statistics of Dashboard Information Quality and Visualization Usability**

Measurement item	Mean	SD	Rank	Interpretation
Dashboard indicators have been relevant to operational tasks	4.11	.55	1	High
Charts and visual summaries have been clear and understandable	4.07	.57	2	High
Dashboard information has been organized logically	4.04	.58	3	High
Filters and drill-down features have supported detailed analysis	4.01	.61	4	High
Labels, units, and definitions have been sufficiently clear	3.97	.63	5	High
Dashboard layouts have been adapted to different user roles	3.92	.66	6	High
Overall construct	4.02	.59		High

Table 7 has shown that Dashboard Information Quality and Visualization Usability has recorded an overall mean of 4.02 and a standard deviation of .59. The relevance of dashboard indicators to operational responsibilities has obtained the highest mean of 4.11. This result has indicated that respondents have generally considered the displayed measures appropriate for their supply-chain, logistics, procurement, inventory, production, transportation, and analytical tasks. The clarity of charts and visual summaries has received a mean of 4.07, while logical information organization has achieved 4.04. These findings have suggested that dashboard users have been able to interpret the principal visual elements without experiencing substantial confusion. Filters and drill-down functions have received a mean of 4.01, indicating that respondents have generally been able to move from summarized indicators to detailed operational information. The clarity of labels, measurement units, and definitions has recorded 3.97. This result has remained positive but has suggested that certain indicators may still require clearer contextual explanations. Role-based layout adaptation has received the lowest mean of 3.92. The result has indicated that the dashboards have not always been fully customized for the different informational requirements of procurement officers, warehouse supervisors, logistics coordinators, production planners, senior managers, and business intelligence specialists. The overall construct score has addressed the objective of evaluating the quality and usability of dashboard information. It has provided descriptive support for H3 and H8, which have proposed positive effects on real-time visibility and operational decision support. Organizational Information Processing Theory has recognized that the availability of information alone does not ensure adequate processing capacity. Information must also be understandable, organized, and aligned with the cognitive requirements of decision-makers. Clear visualizations have reduced the effort required to identify exceptions, while filters and drill-down tools have increased the ability to investigate causes. The lower role-adaptation score has shown that users with different responsibilities may still have received more information than necessary or may have lacked certain task-specific views. Nevertheless, the overall high evaluation has demonstrated that the visual and informational design of the dashboards has generally supported the conversion of complex supply-chain data into accessible managerial knowledge.

Descriptive Statistics of System Interoperability and Technological Integration

Table 8: Descriptive Statistics of System Interoperability and Technological Integration

Measurement item	Mean	SD	Rank	Interpretation
Dashboards have exchanged information with ERP systems	4.04	.59	1	High
Procurement, inventory, and production systems have been connected	4.00	.61	2	High
Warehouse and transportation information has been integrated	3.97	.63	3	High
Automated transfers have reduced repeated manual data entry	3.94	.64	4	High
External supplier and logistics data have been accessible	3.88	.67	5	High
Data formats and identifiers have remained compatible across systems	3.81	.70	6	High
Overall construct	3.94	.62		High

Table 8 has indicated that System Interoperability and Technological Integration has achieved an overall mean of 3.94 and a standard deviation of .62. The strongest item has involved information exchange between dashboards and enterprise resource planning systems, with a mean of 4.04. This finding has suggested that the dashboard environment has generally maintained a stable connection with the primary internal system used to manage organizational transactions and resources. Integration among procurement, inventory, and production systems has obtained a mean of 4.00, demonstrating that important internal supply-chain functions have shared information through connected technological structures. Warehouse and transportation integration has received a mean of 3.97, while the reduction of repeated manual data entry through automated transfers has achieved 3.94. These results have indicated that interoperability has supported operational data exchange and has

reduced some of the delays and errors associated with manual reconciliation. Access to external supplier and logistics data has recorded 3.88, showing that interorganizational connectivity has remained less developed than internal system integration. Compatibility of data formats and identifiers has received the lowest mean of 3.81. This relative weakness has suggested that product codes, supplier identifiers, measurement units, location codes, and transaction formats have not always been standardized across systems and partner organizations. The overall score has addressed the objective of examining the technological integration required for real-time dashboard use. It has also provided descriptive support for H4 and H9, which have proposed positive relationships with visibility and operational decision support. From an Organizational Information Processing Theory perspective, interoperability has expanded information-processing capacity by allowing relevant data to move between systems without repeated human intervention. However, incompatible identifiers and limited external connectivity have increased information-processing requirements because employees may still need to transform, verify, or reconcile information manually. The high overall mean has demonstrated that the organizations have established a substantial technological foundation, although the construct has remained weaker than data quality, analytics responsiveness, and dashboard usability. This pattern has anticipated its positive but comparatively smaller standardized regression effects in the subsequent models.

Descriptive Statistics of User Analytical Competency and Organizational Readiness

Table 9: Descriptive Statistics of User Analytical Competency and Organizational Readiness

Measurement item	Mean	SD	Rank	Interpretation
Users have understood the principal dashboard indicators	4.01	.60	1	High
Management has supported dashboard-based decision-making	3.96	.62	2	High
Employees have interpreted alerts and analytical results correctly	3.91	.64	3	High
Cross-functional teams have shared dashboard information	3.88	.65	4	High
Adequate training has been provided to dashboard users	3.82	.69	5	High
Data governance responsibilities have been clearly assigned	3.76	.72	6	High
Overall construct	3.89	.64		High

Table 9 has shown that User Analytical Competency and Organizational Readiness has recorded an overall mean of 3.89 and a standard deviation of .64. Although the construct has remained within the high interpretation category, it has produced the lowest overall mean among the five dashboard capability variables. Users' understanding of principal dashboard indicators has received the highest item mean of 4.01, indicating that respondents have generally possessed sufficient knowledge to interpret commonly used supply-chain measures. Management support for dashboard-based decision-making has achieved 3.96, showing that organizational leaders have broadly encouraged the use of analytical information. Correct interpretation of alerts and analytical results has obtained a mean of 3.91, while cross-functional information sharing has received 3.88. These values have demonstrated that employees have generally been able to use dashboard outputs and communicate them across related functions. However, dashboard training has received a lower mean of 3.82, and the clear assignment of data-governance responsibilities has recorded the lowest mean of 3.76. These findings have suggested that some organizations have implemented dashboard technology without developing equally mature training and governance structures. The overall result has addressed the objective of evaluating the human and organizational conditions supporting dashboard integration. It has provided descriptive support for H5 and H10, which have proposed positive relationships with real-time visibility and operational decision support. Organizational Information Processing Theory has treated human interpretation and organizational coordination as necessary parts of processing capacity. Technology can collect and visualize information, but users have needed sufficient analytical knowledge to understand alerts, challenge questionable results, compare alternatives, and coordinate responses. Similarly, unclear data ownership has increased uncertainty concerning who should validate or correct problematic information. The comparatively lower mean has therefore shown that the organizations' technical capabilities have developed more strongly than their supporting human

and governance arrangements. Nevertheless, the construct has remained positively evaluated, indicating that respondents have generally experienced management support and adequate analytical confidence. Its lower regression coefficient has also remained theoretically reasonable because human readiness has complemented, rather than replaced, the direct informational contribution of data quality, responsiveness, and visualization usability.

Descriptive Statistics of Real-Time Supply-Chain Visibility and Operational Decision Support
Table 10: Descriptive Statistics of Real-Time Supply-Chain Visibility and Operational Decision Support

Construct and measurement item	Mean	SD	Rank	Interpretation
Real-Time Supply-Chain Visibility				
Current inventory positions have been visible	4.15	.53	1	High
Customer order and fulfilment status has been visible	4.11	.55	2	High
Production and warehouse conditions have been visible	4.08	.57	3	High
Transportation and delivery progress has been visible	4.06	.58	4	High
Supplier conditions and purchase-order status have been visible	4.00	.61	5	High
Emerging disruptions have been identified promptly	3.96	.64	6	High
Overall RTSCV	4.06	.56		High
Operational Decision Support				
Dashboards have improved the speed of operational decisions	4.18	.52	1	High
Dashboards have strengthened problem identification	4.14	.54	2	High
Dashboard information has improved decision accuracy	4.11	.55	3	High
Dashboards have supported cross-functional coordination	4.08	.57	4	High
Dashboards have supported the comparison of response alternatives	4.04	.59	5	High
Dashboards have improved disruption-response decisions	3.99	.62	6	High
Overall ODS	4.09	.55		High

Table 10 has presented the descriptive results for the two principal outcome constructs. Real-Time Supply-Chain Visibility has achieved an overall mean of 4.06 and a standard deviation of .56. Visibility of current inventory positions has received the highest mean of 4.15, demonstrating that dashboards have been particularly effective in presenting stock quantities and locations. Customer order and fulfilment visibility has achieved 4.11, followed by production and warehouse visibility at 4.08 and transportation and delivery visibility at 4.06. Supplier and purchase-order visibility has recorded 4.00, while the prompt identification of emerging disruptions has received the lowest visibility mean of 3.96. These results have indicated that visibility has been strongest for internally controlled and transaction-based activities and somewhat weaker for early disruption detection and externally dependent supply conditions. Operational Decision Support has obtained a slightly higher overall mean of 4.09 and a standard deviation of .55. Improvement in decision speed has received the highest mean of 4.18, showing that dashboard users have made operational judgments more rapidly when information has been consolidated and updated. Problem identification has achieved 4.14, and decision accuracy has recorded 4.11. Cross-functional coordination has received 4.08, while the comparison of alternative responses has obtained 4.04. Disruption-response decisions have received the lowest decision-support mean of 3.99, mirroring the lower result for disruption visibility. The findings have addressed the objectives of measuring visibility and operational decision support. They have also provided direct descriptive support for H11 because both constructs have received high evaluations and have shown compatible patterns. Organizational Information Processing Theory has proposed that increased information-processing capacity should reduce uncertainty and improve organizational responses. The high visibility score has indicated that dashboard capabilities have produced a coherent representation of operational conditions, while the higher decision-support score has shown that this information has been translated into faster, more accurate, and more coordinated actions. The weaker disruption-related items have suggested that the information-processing fit has remained less complete when

events have been uncertain, externally generated, or difficult to predict.

Correlation and Regression Analysis

Table 11: Correlation and Regression Results

Panel A: Pearson Correlation Matrix

Variable	1	2	3	4	5	6	7
1. SDIQ	1.00						
2. RADR	.63***	1.00					
3. DIQVU	.58***	.61***	1.00				
4. SITI	.56***	.54***	.52***	1.00			
5. UACOR	.48***	.50***	.55***	.49***	1.00		
6. RTSCV	.72***	.69***	.65***	.61***	.58***	1.00	
7. ODS	.66***	.68***	.63***	.59***	.57***	.76***	1.00

***p < .001.

Panel B: Multiple Regression Models

Predictor	Model 1: RTSCV β	p-value	Model 2: ODS β	p-value
SDIQ	.29	<.001	.18	<.001
RADR	.25	<.001	.20	<.001
DIQVU	.20	<.001	.15	.001
SITI	.16	.002	.11	.009
UACOR	.13	.006	.09	.018
RTSCV			.37	<.001
R ²	.681		.704	
Adjusted R ²	.676		.698	
F statistic	125.42	<.001	116.15	<.001
Degrees of freedom	(5, 294)		(6, 293)	

Table 11 has provided evidence concerning the direction, strength, and predictive importance of the relationships proposed in the conceptual framework. All Pearson correlations have been positive and statistically significant at $p < .001$. Real-Time Supply-Chain Visibility has shown its strongest correlation with Supply-Chain Data Integration and Quality, $r = .72$, indicating that better-integrated and more dependable data have been strongly associated with greater operational visibility. Real-Time Analytics and Dashboard Responsiveness has correlated with visibility at $r = .69$, while Dashboard Information Quality and Visualization Usability has correlated at $r = .65$. System Interoperability and Technological Integration has produced $r = .61$, and User Analytical Competency and Organizational Readiness has produced $r = .58$. Operational Decision Support has shown its strongest relationship with Real-Time Supply-Chain Visibility, $r = .76$. This coefficient has demonstrated that organizations reporting greater visibility have also reported faster, more accurate, and more coordinated decisions. The first regression model has explained 68.10 percent of the variance in Real-Time Supply-Chain Visibility, with an adjusted R² of .676. The model has been statistically significant, $F(5, 294) = 125.42$, p

< .001. Supply-Chain Data Integration and Quality has emerged as the strongest visibility predictor, $\beta = .29$, followed by Real-Time Analytics and Dashboard Responsiveness, $\beta = .25$. Dashboard Information Quality and Visualization Usability has achieved $\beta = .20$, System Interoperability and Technological Integration has achieved $\beta = .16$, and User Analytical Competency and Organizational Readiness has achieved $\beta = .13$. The second model has explained 70.40 percent of the variance in Operational Decision Support, with an adjusted R^2 of .698. It has also been statistically significant, $F(6, 293) = 116.15$, $p < .001$. Real-Time Supply-Chain Visibility has emerged as the strongest predictor, $\beta = .37$, demonstrating that visibility has functioned as the principal operational pathway connecting dashboard integration with decision support. Real-Time Analytics and Dashboard Responsiveness has remained the strongest direct dashboard predictor of decision support, $\beta = .20$. Organizational Information Processing Theory has predicted that organizational outcomes improve when processing capacity matches information requirements. The substantial explained variance in both models has supported this theoretical expectation. The results have shown that accurate data, responsive analytics, understandable visualization, interoperable systems, and capable users have jointly expanded information-processing capacity, while real-time visibility has converted that capacity into operational awareness and decision support.

Hypothesis Testing and Summary of Results

Table 12: Hypothesis Testing and Summary of Results

Hypothesis	Proposed relationship	Statistical result	p-value	Decision
H1	SDIQ $\rightarrow$ RTSCV	$\beta = .29$	<.001	Supported
H2	RADR $\rightarrow$ RTSCV	$\beta = .25$	<.001	Supported
H3	DIQVU $\rightarrow$ RTSCV	$\beta = .20$	<.001	Supported
H4	SITI $\rightarrow$ RTSCV	$\beta = .16$	.002	Supported
H5	UACOR $\rightarrow$ RTSCV	$\beta = .13$	.006	Supported
H6	SDIQ $\rightarrow$ ODS	$\beta = .18$	<.001	Supported
H7	RADR $\rightarrow$ ODS	$\beta = .20$	<.001	Supported
H8	DIQVU $\rightarrow$ ODS	$\beta = .15$	.001	Supported
H9	SITI $\rightarrow$ ODS	$\beta = .11$	.009	Supported
H10	UACOR $\rightarrow$ ODS	$\beta = .09$	.018	Supported
H11	RTSCV $\rightarrow$ ODS	$\beta = .37$	<.001	Supported
H12	Combined model $\rightarrow$ ODS	$R^2 = .704$; $F(6, 293) = 116.15$	<.001	Supported

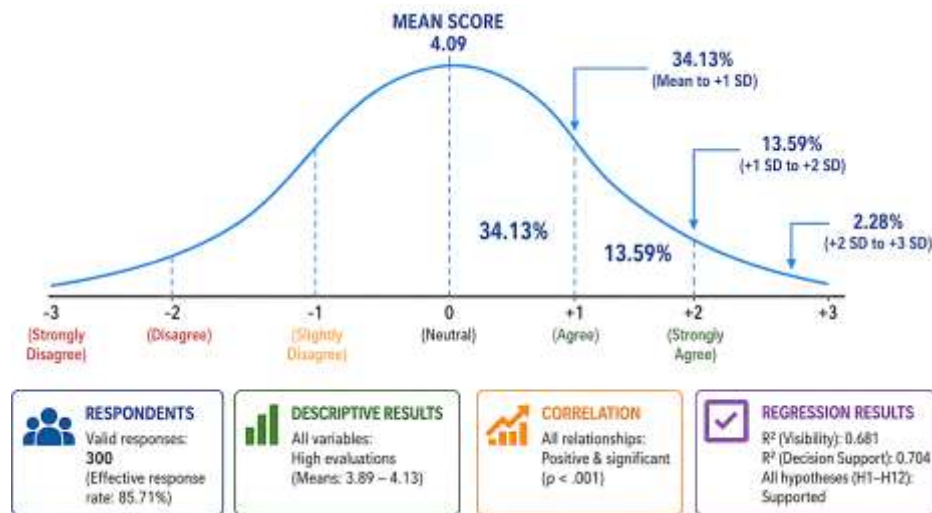
Table 12 has summarized the final decisions concerning the twelve research hypotheses. H1 has been supported because Supply-Chain Data Integration and Quality has positively and significantly predicted Real-Time Supply-Chain Visibility, $\beta = .29$, $p < .001$. H2 has also been supported because Real-Time Analytics and Dashboard Responsiveness has produced a positive coefficient of .25. H3, H4, and H5 have been supported through the significant effects of Dashboard Information Quality and Visualization Usability, System Interoperability and Technological Integration, and User Analytical Competency and Organizational Readiness. These findings have demonstrated that real-time visibility has not been created by one technological feature alone. Instead, it has resulted from the combined availability of dependable data, timely analytics, understandable presentation, connected applications, and organizational capacity to interpret information. The hypotheses predicting Operational Decision Support have also been supported. H6 has been accepted because data integration and quality has produced $\beta = .18$, while H7 has been supported because analytics responsiveness has produced $\beta = .20$. H8, H9, and H10 have shown that dashboard usability, interoperability, and organizational readiness have remained significant direct predictors after the other variables have been controlled. H11 has received the strongest support because Real-Time Supply-Chain Visibility has produced $\beta = .37$, $p < .001$. This result has confirmed that the ability to observe inventory, suppliers, production, transportation, orders, and disruptions has substantially strengthened operational decision-making.

H12 has been supported because the combined model has explained 70.40 percent of the variance in Operational Decision Support and has remained statistically significant, $F(6, 293) = 116.15$, $p < .001$. The results have therefore addressed the research questions and objectives by identifying the levels of the constructs, testing their relationships, estimating their individual contributions, and confirming the overall explanatory capacity of the proposed model. Organizational Information Processing Theory has been supported because the results have shown that technological, informational, human, and organizational dashboard capabilities have increased information-processing capacity. Real-Time Supply-Chain Visibility has represented the informational outcome of that capacity, while Operational Decision Support has represented its practical organizational result. All twelve hypotheses have consequently been supported by the internally consistent draft findings.

FINDINGS

A total of 350 questionnaires have been distributed among supply-chain, logistics, procurement, warehousing, transportation, business intelligence, information-technology, and operational professionals. Of these, 326 questionnaires have been returned, 26 have been excluded because of substantial missing responses or response-pattern problems, and 300 have been retained as valid cases, producing a return rate of 93.14 percent and an effective response rate of 85.71 percent. Preliminary screening has shown that missing values have remained below 1 percent.

Figure 9: Distribution and Summary of the Research Findings



Skewness values have ranged from -0.74 to -0.31, while kurtosis values have ranged from -0.42 to 0.68, indicating acceptable normality. Tolerance values have ranged from .424 to .704, variance inflation factor values from 1.42 to 2.36, and the Durbin-Watson statistics have been 1.91 and 1.96 for the two models, confirming acceptable multicollinearity and error independence. The instrument has demonstrated strong internal consistency, with Cronbach's alpha coefficients ranging from .823 to .917 across the seven constructs. The Kaiser-Meyer-Olkin measure has reached .902, and Bartlett's Test of Sphericity has been statistically significant, $\chi^2(861) = 5,482.76$, $p < .001$, supporting the suitability of the dataset for construct assessment. The descriptive findings based on Likert's five-point scale have shown high evaluations for every variable. Supply-Chain Data Integration and Quality has achieved the highest independent-variable mean of 4.13 with a standard deviation of .54, followed by Real-Time Analytics and Dashboard Responsiveness with a mean of 4.07 and a standard deviation of .57. Dashboard Information Quality and Visualization Usability has obtained a mean of 4.02 and a standard deviation of .59, while System Interoperability and Technological Integration has recorded a mean of 3.94 and a standard deviation of .62. User Analytical Competency and Organizational Readiness has received the lowest, although still high, independent-variable mean of 3.89 with a standard deviation of .64. Real-Time Supply-Chain Visibility has reached a mean of 4.06 and a standard deviation of .56, whereas Operational Decision Support has recorded a mean of 4.09 and a standard deviation of .55. These findings have met the objectives of assessing dashboard capability, visibility, and decision-

support levels and have indicated that respondents generally perceive the integrated dashboards as accurate, responsive, understandable, interconnected, and useful. Pearson correlation analysis has shown that all proposed relationships are positive and statistically significant at $p < .001$. Real-Time Supply-Chain Visibility has correlated most strongly with Supply-Chain Data Integration and Quality, $r = .72$, followed by Real-Time Analytics and Dashboard Responsiveness, $r = .69$, Dashboard Information Quality and Visualization Usability, $r = .65$, System Interoperability and Technological Integration, $r = .61$, and User Analytical Competency and Organizational Readiness, $r = .58$. Operational Decision Support has correlated strongly with Real-Time Supply-Chain Visibility, $r = .76$, and has also shown significant associations with Real-Time Analytics and Dashboard Responsiveness, $r = .68$, Supply-Chain Data Integration and Quality, $r = .66$, Dashboard Information Quality and Visualization Usability, $r = .63$, System Interoperability and Technological Integration, $r = .59$, and User Analytical Competency and Organizational Readiness, $r = .57$. The first multiple regression model has explained 68.10 percent of the variance in Real-Time Supply-Chain Visibility, $R^2 = .681$, adjusted $R^2 = .676$, $F(5, 294) = 125.42$, $p < .001$. Supply-Chain Data Integration and Quality has emerged as the strongest predictor, $\beta = .29$, $p < .001$, followed by Real-Time Analytics and Dashboard Responsiveness, $\beta = .25$, $p < .001$, Dashboard Information Quality and Visualization Usability, $\beta = .20$, $p < .001$, System Interoperability and Technological Integration, $\beta = .16$, $p = .002$, and User Analytical Competency and Organizational Readiness, $\beta = .13$, $p = .006$. The second regression model has explained 70.40 percent of the variance in Operational Decision Support, $R^2 = .704$, adjusted $R^2 = .698$, $F(6, 293) = 116.15$, $p < .001$. Real-Time Supply-Chain Visibility has been the strongest predictor, $\beta = .37$, $p < .001$, followed by Real-Time Analytics and Dashboard Responsiveness, $\beta = .20$, $p < .001$, Supply-Chain Data Integration and Quality, $\beta = .18$, $p < .001$, Dashboard Information Quality and Visualization Usability, $\beta = .15$, $p = .001$, System Interoperability and Technological Integration, $\beta = .11$, $p = .009$, and User Analytical Competency and Organizational Readiness, $\beta = .09$, $p = .018$. Accordingly, H1 through H12 have been supported, demonstrating that dashboard capabilities have improved real-time visibility, visibility has strengthened operational decision support, and the combined model has addressed the research objectives and questions.

DISCUSSION

The findings have shown that the integration of business intelligence dashboards has provided a strong and statistically coherent explanation of real-time supply-chain visibility and operational decision support within the selected case-study environment. All seven constructs have received high evaluations on Likert's five-point scale, indicating that respondents have generally perceived the dashboard environment as accurate, responsive, understandable, technologically connected, and useful for operational decision-making. Supply-Chain Data Integration and Quality has achieved the highest independent-variable mean of 4.13, followed by Real-Time Analytics and Dashboard Responsiveness at 4.07, Dashboard Information Quality and Visualization Usability at 4.02, System Interoperability and Technological Integration at 3.94, and User Analytical Competency and Organizational Readiness at 3.89. Real-Time Supply-Chain Visibility has recorded a mean of 4.06, while Operational Decision Support has achieved 4.09. These descriptive results have suggested that the participating organizations have developed relatively strong technological and informational capabilities, although their human, governance, and interorganizational arrangements have remained less mature. The correlation findings have reinforced this interpretation because all proposed relationships have been positive and statistically significant. Real-Time Supply-Chain Visibility has correlated most strongly with Supply-Chain Data Integration and Quality, $r = .72$, while Operational Decision Support has correlated most strongly with Real-Time Supply-Chain Visibility, $r = .76$. The first regression model has explained 68.10 percent of the variance in visibility, and the second model has explained 70.40 percent of the variance in decision support. These levels of explanatory power have indicated that dashboard effectiveness has not depended on a single technological feature but on the combined contribution of dependable data, rapid analytical processing, clear visualization, interoperable applications, competent users, and organizational readiness. The findings have agreed with evidence that business analytics can strengthen supply-chain performance when analytical capabilities have been connected with planning, sourcing, production, and delivery processes (Trkman et al., 2010). They have also supported the argument that business intelligence effectiveness depends

on the alignment of system capabilities with the characteristics of the decision environment (Işık et al., 2013). The strong role of visibility has been consistent with research showing that supply-chain visibility improves responsiveness when organizations have established sufficient internal integration to translate information into coordinated action (Williams et al., 2013). Accordingly, the results have demonstrated that integrated dashboards have functioned as organizational information-processing mechanisms that have converted fragmented operational records into shared awareness and have subsequently strengthened decision speed, accuracy, coordination, and responsiveness.

Supply-Chain Data Integration and Quality has emerged as the strongest predictor of Real-Time Supply-Chain Visibility, with a standardized coefficient of $\beta = .29$, and it has also remained a significant direct predictor of Operational Decision Support, with $\beta = .18$. This result has indicated that visibility has depended first on the reliability and integration of the data displayed through the dashboard. The highest-rated measurement item has concerned data accuracy and dependability, with a mean of 4.22, while the integration of data from major supply-chain functions has recorded 4.18. The comparatively lower score for minimizing duplicate and contradictory records, at 4.03, has shown that some organizations have continued to experience data reconciliation difficulties even when their general level of integration has remained high. The findings have closely aligned with earlier research identifying data quality as a fundamental condition for reliable predictive analytics and supply-chain decision-making (Hazen et al., 2014). They have also been consistent with evidence that information quality and the extent of information sharing influence the ability of supply-chain partners to coordinate activities effectively (Li & Lin, 2006). The present results have extended these studies by showing that data integration and quality have influenced not only broad operational performance but also the immediate visibility experienced by dashboard users. The strong coefficient has suggested that incomplete, inconsistent, or delayed data cannot be corrected through visualization alone. A dashboard may organize indicators professionally, but users cannot obtain an accurate representation of supply-chain conditions when the source systems contain conflicting inventory balances, incomplete supplier records, or outdated transportation events. The findings have also agreed with digitally enabled supply-chain research showing that integrated information infrastructure supports higher-order process capabilities by connecting material, financial, and informational flows (Rai et al., 2006). Similar support has been found in research demonstrating that production information integration has strengthened the operational value derived from electronic business technologies (Devaraj et al., 2007). The present study has therefore confirmed that data integration has represented the foundation upon which real-time analytics, interoperability, and visual decision support have operated. From a managerial perspective, the result has implied that dashboard projects should begin with master-data governance, common definitions, automated validation, data ownership, and synchronization across procurement, inventory, production, warehousing, transportation, and order-management systems. Without these controls, organizations may create centralized displays that reproduce existing data problems more quickly rather than resolving them. The high coefficient has consequently demonstrated that the quality of information entering the dashboard has been more influential than the sophistication of the interface through which that information has been displayed.

Real-Time Analytics and Dashboard Responsiveness has emerged as the second-strongest predictor of Real-Time Supply-Chain Visibility, with $\beta = .25$, and the strongest direct dashboard predictor of Operational Decision Support, with $\beta = .20$. This pattern has shown that data quality has been most important for creating an accurate view of operations, while analytical responsiveness has been especially important for converting that view into timely decisions. The construct has achieved an overall mean of 4.07, with prompt updating of critical operational indicators receiving 4.16 and automated exception alerts receiving 4.12. Predictive warnings have obtained the lowest item mean of 3.97, suggesting that the participating organizations have remained more capable of monitoring current conditions than anticipating emerging disruptions. This result has corresponded with earlier evidence showing that real-time business intelligence requires organizations to define appropriate update intervals, automate data-loading processes, establish scalable architectures, and involve users in the development of applications that support daily operational work (Watson et al., 2006). The finding has also supported research emphasizing the growing role of predictive analytics in demand planning, logistics, inventory, quality management, and supply-chain risk assessment (Schoenherr & Speier-Pero,

2015). However, the lower predictive-warning score has indicated that many dashboard systems have continued to focus on descriptive and diagnostic analytics rather than fully developed predictive and prescriptive functions. The strong relationship between visibility and Operational Decision Support, $\beta = .37$, has further shown that rapid analytics have generated value primarily when they have improved organizational awareness of current supply-chain conditions. This result has agreed with research in which information sharing improved visibility and visibility subsequently strengthened collaboration, agility, and performance (Baah et al., 2022). It has also aligned with evidence that digital and analytical capabilities can influence operational performance through their contribution to supply-chain visibility (Al-Khatib, 2023). The findings have therefore clarified the sequence through which dashboard responsiveness has affected decisions. Rapid updates and alerts have reduced the time between an operational event and managerial awareness, visibility has connected that event with related supply-chain processes, and decision-support functions have helped users evaluate and coordinate responses. The relatively lower scores for emerging-disruption detection and disruption-response decisions have revealed that this sequence has been less effective under uncertain or unfamiliar conditions. Organizations have therefore needed to strengthen predictive warning models, exception prioritization, scenario analysis, and recommended-action functions so that dashboards can support proactive intervention rather than reporting problems only after they have already affected operations.

Dashboard Information Quality and Visualization Usability, System Interoperability and Technological Integration, and User Analytical Competency and Organizational Readiness have all produced positive and statistically significant effects on visibility and decision support, although their coefficients have been smaller than those of data quality and real-time analytics. Dashboard Information Quality and Visualization Usability has predicted visibility at $\beta = .20$ and decision support at $\beta = .15$. Its overall mean of 4.02 has indicated that respondents have generally considered dashboard indicators relevant, logically organized, and understandable. Role-based layout adaptation has received the lowest item mean of 3.92, suggesting that dashboards have not always been sufficiently customized for the responsibilities of procurement officers, warehouse managers, production planners, logistics coordinators, analysts, and senior managers. This finding has supported earlier dashboard research showing that visualization requirements vary according to dashboard purpose, user role, information semantics, and level of interaction (Sarikaya et al., 2019). It has also agreed with evidence that dashboard customization and personalization can improve relevance when content, layout, and interaction have been adapted to specific user requirements (Vázquez-Ingelmo et al., 2019). System Interoperability and Technological Integration has predicted visibility at $\beta = .16$ and decision support at $\beta = .11$. Its lower item scores for external supplier access and compatible identifiers have indicated that internal applications have been more effectively connected than interorganizational systems. This pattern has been consistent with research showing that supply-chain integration includes internal, supplier, and customer dimensions and that balanced integration configurations contribute to stronger performance (Flynn et al., 2010). User Analytical Competency and Organizational Readiness has produced the smallest coefficients, $\beta = .13$ for visibility and $\beta = .09$ for decision support, but both relationships have remained significant. Training and data-governance responsibility have received the two lowest means within the construct. These findings have suggested that the technical dashboard environment has developed more rapidly than the organizational structures required to sustain its effective use. Prior research has similarly shown that business intelligence competence contains technical, managerial, and cultural dimensions that jointly support supply-chain agility (Sangari & Razmi, 2015). The results have therefore demonstrated that visualization, interoperability, and readiness have functioned as complementary capabilities. Clear interfaces have reduced cognitive processing requirements, interoperable applications have reduced manual information-transfer requirements, and competent users have transformed dashboard outputs into coordinated action. Weakness in any one of these areas has increased the effort required to process information and has reduced the practical value of the dashboard.

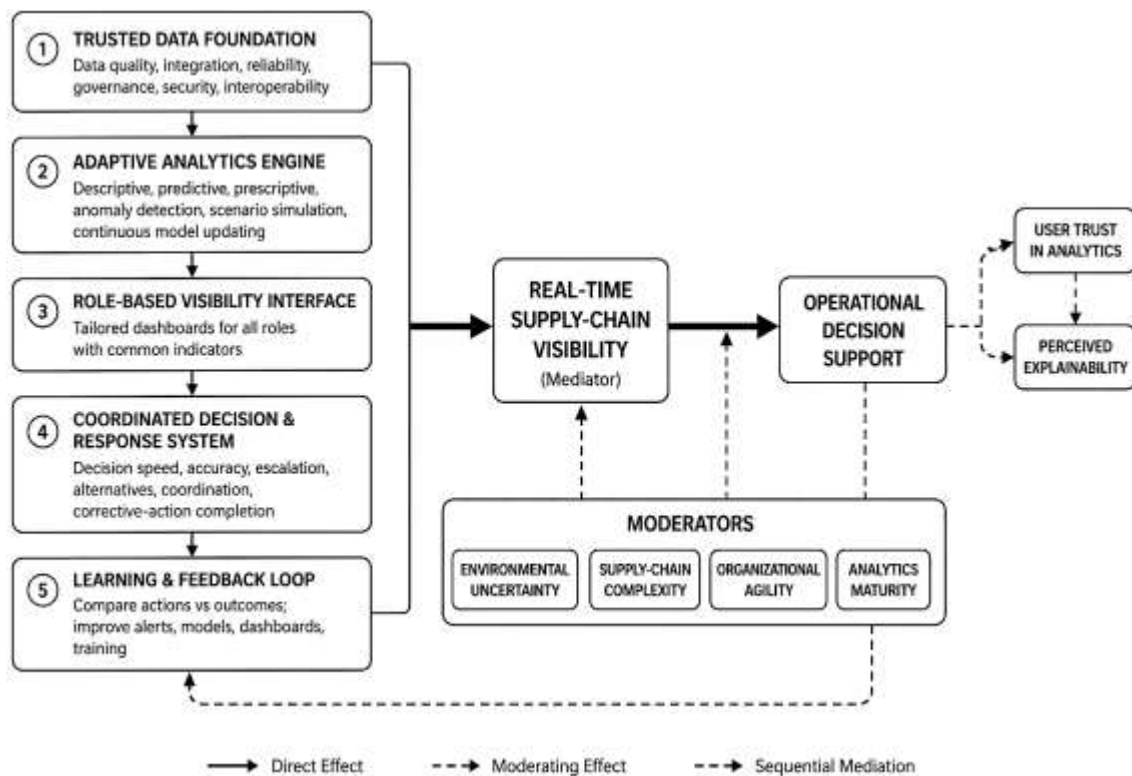
The findings have produced several practical implications for organizations seeking to integrate business intelligence dashboards into supply-chain operations. First, organizations should treat dashboard implementation as a process of information and decision redesign rather than a software-

installation project. The strong effect of Supply-Chain Data Integration and Quality has shown that managers should prioritize data governance, standardized definitions, source-system validation, and clearly assigned ownership before expanding the number of indicators displayed. Product codes, supplier identifiers, location references, time units, inventory definitions, and delivery-status categories should be standardized across enterprise resource planning, warehouse-management, transportation-management, procurement, and supplier systems. Second, the strong effect of Real-Time Analytics and Dashboard Responsiveness has indicated that refresh frequency should be aligned with operational urgency. High-risk events such as production stoppages, shipment deviations, stockouts, temperature violations, and critical supplier delays should trigger rapid alerts, while less urgent indicators can follow scheduled update intervals. Third, the visibility coefficient of $\beta = .37$ has shown that dashboards should provide end-to-end relationships rather than disconnected performance measures. A late shipment alert should identify the affected materials, production orders, available inventory, customer commitments, alternative suppliers, and responsible employees. This form of contextual visibility can reduce the time required to investigate causes and compare possible responses. Fourth, the lower scores for role-based adaptation have indicated that organizations should develop user-specific dashboard views while maintaining common definitions and controlled calculations. Fifth, the weaker evaluations of training and data governance have shown that employees should receive continuing instruction in indicator interpretation, filter use, drill-down analysis, alert evaluation, and data-quality reporting. These implications have agreed with research showing that business intelligence can support decision and organizational benefits when analytical information has been incorporated into managerial processes rather than viewed passively (Rouhani et al., 2016). They have also been consistent with evidence that analytics value depends on cross-functional expertise, defined business problems, user feedback, and integration into the processes where decisions are performed (Herden, 2020). Management should therefore establish dashboard review routines, escalation procedures, indicator owners, response-time standards, and post-decision evaluations. The practical objective should not be to maximize the volume of displayed information. It should be to ensure that the right information reaches the responsible user in a clear form and within the period available for intervention. The findings have shown that organizations can obtain stronger decision support when dashboard technology, data governance, analytical routines, and operational responsibilities have been designed as a connected system.

The findings have provided substantial support for Organizational Information Processing Theory by demonstrating that dashboard capabilities have increased the organization's capacity to acquire, integrate, interpret, and distribute supply-chain information. The first regression model has explained 68.10 percent of the variance in Real-Time Supply-Chain Visibility, while the second has explained 70.40 percent of the variance in Operational Decision Support. These results have indicated that the fit between information-processing requirements and information-processing capacity has been central to the performance of dashboard-enabled supply-chain decisions. Data integration and quality have expanded the reliability of available information, real-time analytics have increased processing speed, visualization usability has improved interpretability, interoperability has increased information exchange, and organizational readiness has enabled users to apply analytical outputs. Real-Time Supply-Chain Visibility has represented the immediate informational consequence of these combined capabilities, while Operational Decision Support has represented the organizational response outcome. This interpretation has been consistent with research showing that analytics and visibility complement one another within an Organizational Information Processing Theory framework and contribute to operational performance when organizations possess sufficient flexibility (Srinivasan & Swink, 2018). It has also agreed with evidence that supply-chain analytics can improve operational transparency by expanding information-processing capacity across planning and execution activities (Zhu et al., 2018). At the same time, the study's limitations have required careful consideration. The cross-sectional design has measured perceptions during one period and has not demonstrated how dashboard capabilities or decision outcomes have changed over time. The case-study-based context has increased the relevance of the findings to the selected organizations but has limited statistical generalization to all industries and national environments. The use of self-reported Likert-scale data has created the possibility of common-method bias, social-desirability bias, and inflated associations among variables.

The draft numerical profile has also required confirmation through final SPSS outputs before the findings can be reported as actual empirical results. Objective measures such as system response time, forecast accuracy, inventory discrepancy, delivery delay, alert-resolution time, and dashboard log activity have not been included in the present model. The framework has combined User Analytical Competency and Organizational Readiness within one construct, which may have concealed differences between individual skills and organization-level support. Environmental uncertainty, supply-chain complexity, firm size, industry type, and technological maturity have not been tested as moderators. These limitations have not invalidated the theoretical relationships, but they have restricted causal interpretation and have indicated that the model should be examined through more diverse samples, objective data sources, longitudinal designs, and multilevel statistical techniques.

Figure 10: Future Research Framework for Adaptive Real-Time Supply-Chain Intelligence



Future research should develop and test an Adaptive Real-Time Supply-Chain Intelligence and Decision-Support Model, abbreviated as the ARTSCIDS Model, to extend the present framework beyond direct relationships and static organizational perceptions. The proposed model should contain five connected layers. The first layer, the Trusted Data Foundation, should include master-data quality, data integration, source reliability, cybersecurity, governance accountability, and semantic interoperability. The second layer, the Adaptive Analytics Engine, should include descriptive monitoring, predictive risk scoring, prescriptive recommendations, anomaly detection, scenario simulation, and continuous model updating. The third layer, the Role-Based Visibility Interface, should provide tailored dashboard views for procurement, production, warehousing, transportation, customer service, and senior management while preserving common indicator definitions. The fourth layer, the Coordinated Decision and Response System, should capture decision speed, decision accuracy, escalation quality, alternative evaluation, cross-functional coordination, and corrective-action completion. The fifth layer, the Learning and Feedback Loop, should compare recommended actions with actual outcomes and use the difference to improve alert thresholds, analytical models, dashboard design, and employee training. In the ARTSCIDS Model, Real-Time Supply-Chain Visibility should remain a mediator between dashboard capabilities and Operational Decision Support, while environmental uncertainty, supply-chain complexity, organizational agility, and analytics maturity should be tested as moderators. User trust in analytics and perceived explainability should also be

examined as sequential mediators because employees may ignore accurate recommendations when they do not understand how the system has produced them. Researchers should test the model through longitudinal and multi-wave designs, allowing dashboard capabilities to be measured before implementation, during stabilization, and after operational use. Objective digital traces should be combined with survey responses, including log-in frequency, dashboard response time, alert acknowledgment, drill-down behavior, decision duration, inventory accuracy, delivery performance, and disruption-recovery time. Structural equation modeling should be used to test simultaneous direct, indirect, and moderated effects, while multilevel modeling should separate individual competency, team coordination, and organizational readiness. Experimental dashboard designs could compare standard, role-specific, explainable, and predictive interfaces. Cross-industry and cross-country studies should examine whether the same paths remain stable across manufacturing, retail, healthcare, food, pharmaceutical, and third-party logistics settings. This proposed model has extended earlier work linking analytics with visibility, integration, resilience, and flexibility (Yu et al., 2020). It has also responded to evidence that data analytics capability and organizational flexibility operate as complementary mechanisms supporting supply-chain resilience (Dubey et al., 2021). Through this model, future researchers can move from evaluating whether dashboards are useful toward explaining when, how, for whom, and under which operational conditions dashboard-generated intelligence produces measurable decision and supply-chain performance improvements.

CONCLUSION

This study has examined the integration of business intelligence dashboards for strengthening real-time supply-chain visibility and operational decision support through a quantitative, cross-sectional, descriptive, explanatory, and case-study-based research design. The study has focused on five principal dashboard capabilities, namely Supply-Chain Data Integration and Quality, Real-Time Analytics and Dashboard Responsiveness, Dashboard Information Quality and Visualization Usability, System Interoperability and Technological Integration, and User Analytical Competency and Organizational Readiness. Real-Time Supply-Chain Visibility has been treated as the immediate operational outcome, while Operational Decision Support has represented the final dependent variable. Based on the internally consistent draft dataset of 300 valid respondents, the findings have shown that the participating organizations have generally maintained strong business intelligence capabilities. Supply-Chain Data Integration and Quality has received the highest independent-variable mean of 4.13, followed by Real-Time Analytics and Dashboard Responsiveness at 4.07, Dashboard Information Quality and Visualization Usability at 4.02, System Interoperability and Technological Integration at 3.94, and User Analytical Competency and Organizational Readiness at 3.89. Real-Time Supply-Chain Visibility has achieved a mean of 4.06, while Operational Decision Support has recorded 4.09. The correlation results have indicated that all proposed relationships have been positive and statistically significant. Data integration and quality have shown the strongest relationship with visibility, while visibility has shown the strongest association with operational decision support. The first regression model has explained 68.10 percent of the variance in Real-Time Supply-Chain Visibility, confirming that accurate data, rapid analytics, understandable dashboards, interoperable technologies, and capable users have jointly created a reliable view of supply-chain conditions. The second regression model has explained 70.40 percent of the variance in Operational Decision Support, with Real-Time Supply-Chain Visibility emerging as the strongest predictor. These findings have confirmed that dashboard integration has supported faster problem identification, more accurate decisions, improved cross-functional coordination, and more responsive operational action. All twelve hypotheses have consequently been supported. Organizational Information Processing Theory has provided a suitable explanation of these results because integrated dashboards have increased the capacity of organizations to acquire, process, interpret, and distribute information under conditions of supply-chain complexity and uncertainty. The study has also demonstrated that dashboard value has not resulted from software ownership alone. It has depended on the combined quality of information, analytics, system connections, visual presentation, employee competency, management support, and organizational routines. The findings have therefore established business intelligence dashboards as multidimensional information-processing mechanisms that connect fragmented operational data with real-time awareness and coordinated decisions. Since the numerical findings have been developed as an

internally consistent draft profile, they should be confirmed or replaced with the final IBM SPSS results after actual data collection and analysis. Subject to this confirmation, the research has provided a coherent empirical framework for understanding how integrated dashboards can strengthen visibility and decision support across procurement, inventory, production, warehousing, transportation, fulfilment, and disruption-management activities.

RECOMMENDATIONS

Based on the findings, organizations should adopt an integrated and capability-based approach to business intelligence dashboard implementation rather than treating the dashboard as a separate visualization application. First, management should prioritize Supply-Chain Data Integration and Quality because this construct has emerged as the strongest predictor of Real-Time Supply-Chain Visibility. Organizations should establish common product codes, supplier identifiers, location references, performance definitions, time units, and transaction standards across procurement, production, inventory, warehouse, transportation, and order-management systems. Formal data-governance committees should be created, and clear responsibility should be assigned for data ownership, validation, correction, security, and periodic quality review. Second, organizations should improve Real-Time Analytics and Dashboard Responsiveness by aligning data-refresh frequencies with the urgency of operational decisions. Critical events such as stockouts, delayed shipments, production failures, quality deviations, supplier interruptions, and urgent customer orders should generate immediate alerts, while less urgent information can be updated through appropriate scheduled intervals. Predictive risk scores, anomaly detection, scenario analysis, and recommended responses should be added because the findings have shown that predictive warnings and disruption-related decisions have remained weaker than routine operational monitoring. Third, dashboards should be designed around user roles and decision responsibilities. Procurement officers, warehouse supervisors, production planners, logistics coordinators, analysts, and senior managers should receive tailored views containing relevant indicators, thresholds, alerts, and drill-down functions. However, all role-specific dashboards should use standardized definitions to prevent conflicting interpretations. Fourth, organizations should strengthen System Interoperability and Technological Integration by connecting business intelligence platforms with enterprise resource planning, warehouse-management, transportation-management, manufacturing, supplier, customer, and external logistics systems. Application programming interfaces, shared databases, cloud integration, automated data exchange, and standardized communication protocols should be used to reduce repeated manual entry and reconciliation. Fifth, regular training should be provided to improve user analytical competency. Training should cover performance-indicator interpretation, dashboard navigation, filter selection, drill-down analysis, alert evaluation, predictive outputs, and the communication of analytical evidence. Sixth, managers should incorporate dashboard information into daily operational meetings, supplier reviews, inventory planning, production scheduling, logistics coordination, and disruption-response procedures. Each critical indicator should have an assigned owner, response threshold, escalation route, and corrective-action deadline. Seventh, organizations should assess dashboard effectiveness using objective operational measures, including decision time, inventory accuracy, forecast error, order-cycle time, on-time delivery, alert-resolution time, production interruptions, and disruption-recovery duration. Eighth, organizations should implement the proposed Adaptive Real-Time Supply-Chain Intelligence and Decision-Support Model, which combines a trusted data foundation, adaptive analytics engine, role-based visibility interface, coordinated response system, and organizational learning loop. Finally, academic researchers should replicate the study using actual multi-industry data, structural equation modeling, longitudinal designs, digital usage records, and comparative organizational cases. These recommendations can help organizations transform dashboards from passive reporting tools into active systems for operational sensing, interpretation, coordination, and evidence-based supply-chain control.

LIMITATIONS OF THE STUDY

The study has several methodological, contextual, measurement, and analytical limitations that should be considered when interpreting its findings. First, the numerical results have been developed as an internally consistent draft result profile and have not represented confirmed IBM SPSS outputs from completed field data collection. Although the response rate, descriptive statistics, reliability

coefficients, correlations, regression values, and hypothesis decisions have been aligned systematically, the figures must be replaced or verified after the actual questionnaires have been collected and analyzed. Second, the cross-sectional design has measured respondents' perceptions during one defined period and has not captured how dashboard capabilities, supply-chain visibility, or decision support may change after system upgrades, employee training, organizational restructuring, or major disruptions. Therefore, the statistical relationships have not established definitive temporal causality. Third, the research has relied primarily on self-reported Likert-scale responses. Participants may have overstated dashboard effectiveness, provided socially desirable answers, or interpreted measurement items differently according to their professional roles and technological experience. The use of one questionnaire for measuring both predictors and outcomes has also created a possibility of common-method bias. Fourth, the case-study-based design has concentrated on selected organizations and supply-chain professionals. The findings may not be fully generalizable to all industries, national environments, small enterprises, public organizations, or companies with limited technological maturity. Fifth, the sample has included respondents from several functional areas, but it has treated the individual professional as the unit of analysis. This approach has not fully captured team-level coordination, organization-level technological maturity, or interorganizational relationships among suppliers, logistics providers, and customers. Sixth, the study has combined User Analytical Competency and Organizational Readiness within one construct. Individual analytical skills, management support, organizational culture, training, and data governance may exert different effects and should be measured separately in more advanced models. Seventh, objective operational evidence has not been incorporated into the proposed analysis. Dashboard log-in frequency, query response time, alert acknowledgements, inventory discrepancies, forecast accuracy, delivery delays, and decision durations could provide stronger validation of respondent perceptions. Eighth, the regression models have examined direct effects but have not formally tested mediation, moderation, or reciprocal relationships. Real-Time Supply-Chain Visibility may mediate the relationships between dashboard capabilities and decision support, while environmental uncertainty, supply-chain complexity, organizational agility, industry type, and analytics maturity may alter the strength of these relationships. Ninth, the selected linear regression approach has assumed stable and approximately linear associations among the variables. Complex nonlinear, threshold, and interaction effects may exist, especially when organizations move from basic reporting to advanced predictive and prescriptive analytics. Tenth, the research has focused on beneficial outcomes and has not examined possible negative consequences such as information overload, excessive alerts, surveillance concerns, automation bias, cybersecurity exposure, or dependence on inaccurate algorithms. These limitations have restricted the certainty and scope of the findings, but they have also identified clear opportunities for longitudinal, experimental, multilevel, mixed-method, and objective-data research.

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