Journal of Sustainable Development and Policy

Volume: 5; **Issue:** 2
Pages: 01-51

Design of an Economic Decision Intelligence Platform for Resource Optimization in Socially Impactful U.S. Sectors

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Doi: 10.63125/a4023t75
Received: 12 March 2026; **Revised:** 21 April 2026; **Accepted:** 21 May 2026; **Published:** 02 June 2026;

Abstract

Organizations operating across socially impactful U.S. sectors increasingly depend on data analytics, artificial intelligence, and decision-support technologies, yet fragmented information systems, limited forecasting capability, inefficient resource allocation, delayed decision processes, and competing service demands continue to constrain effective resource optimization. This study aimed to design and quantitatively evaluate an Economic Decision Intelligence Platform capable of integrating organizational data, predictive analytics, AI-supported optimization, and real-time decision support to improve Resource Optimization Performance. A quantitative, cross-sectional, case-study-based research design was employed using organizational cases drawn from healthcare, education, public utilities, energy, infrastructure, social services, and other public-interest environments in the United States. The final analytical sample comprised 306 valid responses from 340 distributed questionnaires, representing a 90.0% usable response rate. The principal variables were Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, Real-Time Decision Support Intelligence, and Resource Optimization Performance. Analysis included descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple regression, ANOVA, standardized beta coefficients, tolerance, VIF, and Durbin-Watson diagnostics. The reported quantitative findings showed that Resource Optimization Performance achieved the highest overall mean, $M = 4.14$, $SD = 0.55$, while AI-Driven Resource Allocation and Optimization recorded the highest predictor mean, $M = 4.11$, $SD = 0.57$. All predictors were significantly associated with Resource Optimization Performance, including Integrated Economic Data Intelligence, $r = .66$, Predictive Economic Analytics, $r = .63$, AI-Driven Resource Allocation and Optimization, $r = .74$, and Real-Time Decision Support Intelligence, $r = .70$, all $p < .001$. The combined model explained 70.9% of the variance in Resource Optimization Performance, $R = .842$, $R^2 = .709$, adjusted $R^2 = .705$, $F(4, 301) = 183.34$, $p < .001$. AI-Driven Resource Allocation and Optimization emerged as the strongest independent predictor, $\beta = .31$, followed by Real-Time Decision Support Intelligence, $\beta = .27$, Predictive Economic Analytics, $\beta = .24$, and Integrated Economic Data Intelligence, $\beta = .22$. All five hypotheses were supported. The findings imply that socially impactful organizations can improve resource utilization, demand matching, cost control, and allocation efficiency by integrating reliable data, predictive intelligence, AI-supported optimization, and timely managerial decision support within a unified platform

Keywords

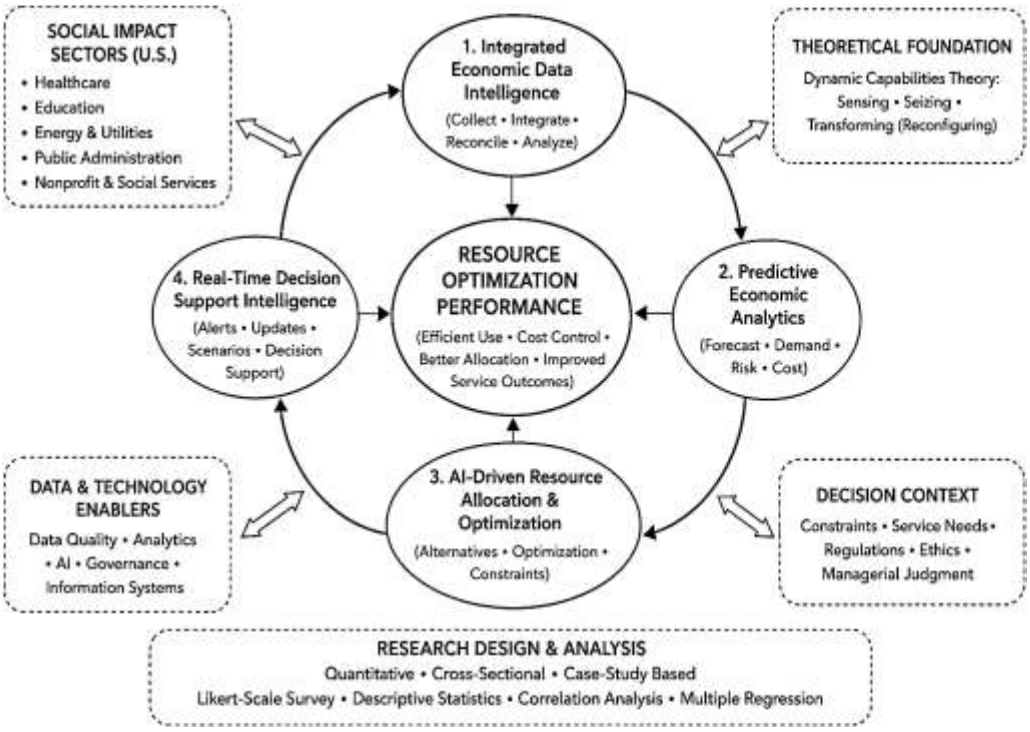
Economic Decision Intelligence; Resource Optimization; Artificial Intelligence; Predictive Analytics; Real-Time Decision Support

INTRODUCTION

Economic decision intelligence can be defined as the systematic integration of organizational data, analytical models, artificial intelligence, decision-support mechanisms, and managerial judgment to improve the accuracy, consistency, timeliness, and economic efficiency of decisions involving scarce resources. The concept is closely associated with the development of decision support systems, which have historically focused on the use of computerized technologies to help individuals and organizations structure complex problems, compare alternatives, process large quantities of information, and select appropriate actions under conditions of uncertainty and resource limitations (Arnott & Pervan, 2005). Data-driven decision support has further emphasized the role of organizational databases, information-processing technologies, analytical systems, and performance-monitoring tools in converting organizational information into useful evidence for managerial decision-making (Power, 2008). The emergence of business intelligence and business analytics has substantially expanded this orientation by combining data management, statistical analysis, predictive modeling, visualization, and organizational information systems to transform heterogeneous data into knowledge capable of supporting strategic and operational decisions (Chen et al., 2012). Business analytics can therefore be viewed as an evidence-oriented process through which organizations identify problems, evaluate available information, generate analytical insight, and select appropriate responses rather than as a purely technological procedure for manipulating data (Holsapple et al., 2014). Within the context of the present study, an Economic Decision Intelligence Platform refers to an integrated organizational platform through which economic, financial, operational, workforce, demand, service, asset, and contextual information can be collected, integrated, analyzed, predicted, and translated into resource-allocation decisions. This definition extends conventional business intelligence because the proposed platform incorporates predictive analytics, artificial intelligence, optimization mechanisms, real-time decision support, and organizational judgment within a unified decision structure. Such an approach has substantial international relevance because governments, healthcare systems, educational institutions, public utilities, infrastructure organizations, nonprofit entities, and social-service providers frequently operate under financial constraints, changing service demands, fragmented information systems, and competition for limited organizational resources. The rapid accumulation of digital information has also increased the volume, variety, and complexity of data available to decision-makers, strengthening the importance of analytical approaches capable of converting extensive structured and unstructured datasets into useful organizational knowledge (Gandomi & Haider, 2015). Economic decision intelligence can therefore be situated at the intersection of decision science, information systems, artificial intelligence, organizational management, economics, and resource optimization, where the organizational value of data depends on its ability to support decisions concerning the allocation and utilization of limited resources.

The effectiveness of economic decision intelligence is strongly associated with the quality, accessibility, integration, and organizational usability of data because large quantities of information do not automatically produce better resource decisions. Organizations across socially impactful sectors continuously generate financial records, service-demand information, workforce data, asset information, budgetary records, performance indicators, operational statistics, and contextual information, yet these data may remain fragmented across departments or technological systems. Information quality, system quality, and service quality have been identified as important determinants of the organizational impact generated through information systems, demonstrating that the usefulness of technology depends partly on the reliability and usability of the information that it produces (Gorla et al., 2010). The effectiveness of analytical decision-making has also been linked to the maturity of business intelligence systems, the quality of organizational information, and the development of a culture in which decision-makers actively use analytical evidence in organizational processes (Popovic et al., 2012). These findings are particularly relevant to Integrated Economic Data Intelligence because resource optimization requires an organization to combine previously separated financial, operational, human-resource, service, and demand information into a coherent analytical environment. Big-data analytics capability has accordingly been conceptualized as a multidimensional organizational capability involving technological resources, human expertise, managerial skills, data availability, and coordinated organizational processes rather than merely the possession of advanced software or extensive datasets (Gupta & George, 2016). Business intelligence research has similarly shown that organizations obtain value when information-system investments are transformed into useful analytical assets and subsequently embedded within managerial and operational processes (Trieu, 2017). The analytical use of integrated information is further affected by challenges related to data volume, variety, velocity, quality, security, governance, methodological selection, and interoperability, all of which influence whether large datasets can be converted into reliable decision inputs (Sivarajah et al., 2017). Empirical research among European organizations has also demonstrated that big-data analytics can generate organizational value when analytical resources are combined with knowledge-related and organizational capabilities (Corte-Real et al., 2017). Integrated Economic Data Intelligence within the proposed platform can therefore be understood as the organizational capability to collect, reconcile, contextualize, and analyze multiple categories of information so that decision-makers can evaluate costs, available resources, demand pressures, utilization patterns, service requirements, and operational constraints within a common analytical structure. This capability is especially important in socially impactful sectors because decisions regarding personnel, facilities, budgets, infrastructure, equipment, educational resources, healthcare capacity, or public services often require simultaneous consideration of economic efficiency and service availability.

Figure 1: Economic Decision Intelligence Framework for Resource Optimization Performance



A second major component of economic decision intelligence involves the transition from descriptive information toward predictive and prescriptive analytical processes. Descriptive analytics primarily identifies what has occurred within an organization, while predictive analytics estimates probable outcomes by identifying statistical relationships, historical patterns, and emerging conditions. Prescriptive analytics extends this process by connecting predictive information with alternative actions, resource constraints, optimization criteria, and organizational objectives. Predictive Economic Analytics within the present study refers to the organizational capability to employ historical information, statistical methods, machine-learning techniques, scenario data, and contextual variables to estimate future resource requirements, demand conditions, operating costs, financial pressures, risk exposures, service volumes, and performance outcomes. Prediction becomes economically valuable when it contributes directly to organizational action rather than remaining an isolated forecasting exercise. Research connecting machine learning with operations research has demonstrated that predictive information can be incorporated into optimization models so that organizations can move from estimating possible outcomes toward identifying actions that are suitable under particular predicted conditions (Bertsimas & Kallus, 2020). This connection is fundamental to an Economic Decision Intelligence Platform because accurate predictions regarding demand, cost, or resource availability should ultimately support better allocation decisions. Artificial intelligence also changes the relationship between analytical systems and organizational decision-makers because algorithmic technologies can process information and identify patterns at a scale that exceeds conventional human information-processing capacity, while human judgment remains important when organizational problems contain ambiguity, contextual requirements, competing goals, or social considerations (Jarrahi, 2018). The introduction of AI into organizational decision structures can also alter the distribution of decision authority, the speed with which decisions are made, and the range of alternatives that can be examined (Shrestha et al., 2019). This relationship becomes particularly significant in socially impactful sectors, where an optimization model may identify an economically efficient allocation of personnel, funding, assets, or facilities, but organizational decision-makers must evaluate whether the recommendation is appropriate within service, regulatory, ethical, and institutional constraints. The relationship between automation and augmentation has consequently been described as an organizational paradox in which AI may both replace specific analytical activities and enhance the capabilities of human decision-makers (Raisch & Krakowski, 2021). Analytical capabilities also become more valuable when they are integrated with dynamic and operational organizational capabilities rather than treated as isolated technological resources (Mikalef et al., 2020). Predictive Economic Analytics within this research therefore represents one stage of an integrated decision process through which data are transformed into estimates, estimates are connected with alternative resource configurations, and analytical outputs become available for managerial evaluation and organizational action.

The international significance of economic decision intelligence becomes particularly visible in sectors where resource-allocation decisions directly influence essential services, public welfare, organizational accessibility, and the functioning of critical social systems. Healthcare organizations represent a prominent example because hospitals, clinics, health systems, and related institutions must allocate financial resources, healthcare professionals, beds, diagnostic facilities, medical equipment, operating-room capacity, pharmaceuticals, and other resources under fluctuating demand and financial pressure. Big-data analytics in healthcare has been identified as an important mechanism for extracting organizational and clinical knowledge from complex datasets and supporting efforts to improve the coordination of services, cost management, and organizational decision processes (Raghupathi & Raghupathi, 2014). Healthcare analytics capabilities have also been associated with predictive modeling, decision support, pattern recognition, traceability, and the analysis of structured and unstructured information, indicating that analytical platforms can connect data infrastructure with operational and managerial decision-making (Wang et al., 2018). Educational institutions experience comparable resource-allocation challenges because universities, colleges, schools, and educational agencies must distribute faculty capacity, classroom resources, instructional technologies, student-support services, financial budgets, facilities, and administrative resources among competing academic and institutional requirements. Big data and analytics have consequently been examined as mechanisms for understanding complex educational environments and supporting institution-level decisions related to performance and resource management (Daniel, 2015). Learning-analytics research has also demonstrated the extensive use of educational data to understand learning behavior, student engagement, educational processes, and institutional decision environments (Viberg et al., 2018). Similar decision challenges can be observed within the energy and utility sectors, where resource decisions must balance generation capacity, infrastructure utilization, demand conditions, reliability, operating costs, and customer requirements. Demand-response mechanisms and smart-grid technologies have been associated with the coordination of electricity consumption and improvements in the efficiency of energy-system operations (Siano, 2014). Big-data approaches within smart energy management have also been applied to areas including generation management, renewable-energy integration, asset management, system operations, and demand-side management (Zhou et al., 2016). Public administration presents another major setting because government agencies collect large amounts of administrative, service, citizen, sensor, financial, and operational information that can support the monitoring of social programs and public services (Mergel et al., 2016). Across these diverse international settings, the underlying economic challenge is structurally similar: organizations must allocate limited resources among multiple competing demands while maintaining appropriate levels of service performance. This common structure provides a strong basis for studying economic decision intelligence as a cross-sector resource-management capability.

Artificial intelligence has become increasingly relevant to economic and administrative decision environments because organizational decisions frequently involve large datasets, multiple alternatives, competing constraints, and requirements for rapid evaluation. Within socially impactful sectors, however, resource optimization extends beyond simple cost reduction because decision-makers must frequently consider service accessibility, operational capacity, public value, accountability, institutional requirements, and the distribution of limited organizational resources. Research on artificial intelligence in the public sector has identified applications involving administrative automation, resource management, service provision, risk analysis, monitoring, prediction, and decision support while also documenting organizational, technological, legal, and governance challenges associated with the use of AI in public institutions (Wirtz et al., 2019). Integrated frameworks for artificial intelligence in public management have similarly connected technological capabilities with organizational structures, managerial processes, and governance arrangements, emphasizing that effective AI-supported decision-making requires institutional coordination rather than isolated technological implementation (Wirtz & Muller, 2019). These observations are highly relevant to the proposed Economic Decision Intelligence Platform because optimization within healthcare, education, utilities, infrastructure, public agencies, or social services cannot be reduced to the mathematical minimization of expenditure. Resource decisions may simultaneously involve cost efficiency, service quality, capacity availability, workforce requirements, program coverage, and institutional constraints. Systematic research on artificial intelligence in public governance has identified several potential organizational functions involving information processing, efficiency, service provision, decision-making, monitoring, and administrative support, while also showing that empirical knowledge regarding many public-sector applications remains uneven (Zuiderwijk et al., 2021). More recent empirical work has shown that citizens may evaluate AI-supported governmental decisions differently depending on whether AI serves an advisory or autonomous decision-making role, indicating that the configuration of human involvement remains important in socially consequential decision processes (Haesevoets et al., 2024). Research examining AI-driven decision-making in public-sector environments has also identified potential mismatches between conventional machine-learning assumptions and actual public decisions, including difficulties associated with biased historical labels, distribution shifts, multiple objectives, previous institutional decisions, and human participation (Fischer-Abaigar et al., 2024). Systematic research concerning AI and governmental functions has likewise documented a broad range of administrative applications alongside organizational and decision-related challenges (Alshahrani et al., 2024). These findings support the inclusion of Real-Time Decision Support Intelligence as a distinct capability within the proposed platform. Such intelligence refers to the ability to provide managers with continuously updated information, analytical outputs, alerts, scenario assessments, and resource-allocation alternatives at points where operational or economic adjustments are required.

Resource optimization refers to the coordinated allocation, utilization, monitoring, and reconfiguration of organizational resources in ways that improve the achievement of defined economic and operational objectives within existing constraints. Resources within socially impactful organizations may include budgets, personnel, facilities, infrastructure, equipment, technological systems, inventory, energy, service capacity, time, information, and other organizational assets. Economic decision intelligence therefore requires more than the production of analytical information because organizations must also possess the ability to translate information into changes in resource configuration and organizational action. Dynamic Capabilities Theory provides an appropriate theoretical foundation for understanding this process because it explains how organizations respond to changing conditions through activities associated with sensing relevant developments, seizing appropriate responses, and transforming or reconfiguring organizational resources (Teece, 2007). Applied to the present study, Integrated Economic Data Intelligence can contribute to sensing by providing visibility into economic conditions, operational requirements, resource availability, utilization patterns, and service demand. Predictive Economic Analytics can assist organizations in identifying expected demand, emerging risks, cost pressures, capacity requirements, and potential performance conditions. AI-Driven Resource Allocation and Optimization can support the evaluation of alternative resource combinations according to organizational constraints and objectives. Real-Time Decision Support Intelligence can provide managers with current information and analytical recommendations that support adjustments when organizational conditions change. Empirical research on analytics capabilities reinforces this capability-based interpretation. Big-data analytics capability has been found to be multidimensional, while alignment between analytics capability and organizational strategy has been associated with stronger organizational performance (Akter et al., 2016). Process-oriented dynamic capabilities have also been shown to mediate the relationship between big-data analytics capability and firm performance, indicating that analytical resources create value through organizational processes that convert analytical insight into action (Wamba et al., 2017). Evidence from European firms has similarly connected big-data analytics with organizational knowledge and dynamic capabilities in the creation of business value (Corte-Real et al., 2017). Research has also shown that different combinations of analytics resources and organizational conditions may be associated with performance outcomes, suggesting that technological assets must operate within broader organizational configurations (Mikalef et al., 2019a). Big-data analytics capabilities have additionally been associated with dynamic capabilities and organizational innovation, reinforcing the argument that analytical systems can contribute to the reconfiguration of organizational resources and processes (Mikalef et al., 2019b). Resource Optimization Performance in this study can therefore be represented through efficient utilization, reduced resource waste, improved allocation accuracy, stronger capacity use, better cost control, improved matching of resources to demand, and more coordinated deployment of organizational assets.

Within the United States, resource optimization in socially impactful sectors involves a complex combination of economic, technological, managerial, and service-related considerations. Healthcare institutions coordinate clinical and administrative capacity, educational organizations manage instructional and institutional resources, utilities and energy organizations balance infrastructure with changing demand, and public or nonprofit organizations allocate financial and operational resources across programs serving different communities and service requirements. Existing research has demonstrated the relevance of analytics within healthcare environments and has identified its capacity to support organizational decision-making through the analysis of complex clinical, operational, and administrative information (Raghupathi & Raghupathi, 2014; Wang et al., 2018). Research in education has similarly identified the use of data and analytics for understanding institutional processes, student activities, organizational performance, and educational decision environments (Daniel, 2015; Viberg et al., 2018). Public-administration research has examined the use of large datasets and artificial intelligence for administrative analysis, monitoring, service delivery, and organizational decision support (Mergel et al., 2016; Wirtz et al., 2019). Research in energy and utility environments has also shown that demand information and large-scale operational data can support resource coordination, infrastructure management, and system efficiency (Siano, 2014; Zhou et al., 2016). At the organizational level, analytics research has established significant connections among analytical capability, strategy alignment, dynamic capabilities, innovation, and organizational performance (Akter et al., 2016; Wamba et al., 2017). Other studies have demonstrated that effective analytical capability depends on combinations of data, technological resources, managerial resources, human expertise, and organizational processes (Gupta & George, 2016; Mikalef et al., 2020). Existing scholarship nevertheless commonly examines individual sectors, separate technological applications, general business-performance outcomes, or isolated analytical capabilities rather than an integrated economic decision structure connecting data integration, prediction, optimization, real-time decision support, and resource optimization across socially impactful organizational contexts. Public-sector AI research has also identified substantial differences among organizational settings and has emphasized the importance of matching AI capabilities with actual institutional decision structures and administrative objectives (Fischer-Abaigar et al., 2024; Zuiderwijk et al., 2021). The present study is therefore structured as a quantitative, cross-sectional, case-study-based investigation involving selected socially impactful U.S. sectors. The proposed Economic Decision Intelligence Platform is represented through four explanatory dimensions: Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence. Resource Optimization Performance is treated as the dependent variable. A five-point Likert-scale questionnaire has been used to measure the study constructs, descriptive statistics have assessed the observed levels of the variables, Pearson correlation analysis has examined the direction and strength of relationships among the constructs, and multiple regression analysis has determined the individual and combined statistical effects of the Economic Decision Intelligence dimensions on Resource Optimization Performance.

Background of the Study

The increasing complexity of economic decision-making in socially impactful sectors has created a strong need for integrated systems capable of transforming large volumes of organizational data into timely, accurate, and actionable resource-allocation decisions. Organizations operating in healthcare, education, public utilities, energy, social services, infrastructure, community development, and other socially important sectors are continuously required to distribute limited financial, human, technological, physical, and informational resources among competing operational needs. The effectiveness of these decisions directly affects organizational efficiency, service availability, budget utilization, workforce productivity, infrastructure capacity, and the quality of services delivered to communities. Traditional resource-allocation processes have often depended on fragmented information systems, historical reports, managerial experience, departmental estimates, and periodic financial reviews. Although these approaches remain important, they may not provide sufficient analytical support when decision environments involve rapidly changing demand, multiple constraints, interconnected organizational processes, and extensive amounts of structured and unstructured data. Economic Decision Intelligence offers a more integrated approach by combining economic data, organizational information, predictive analytics, artificial intelligence, optimization mechanisms, and real-time decision support within a unified platform. In such an environment, managers can examine current resource conditions, identify patterns in organizational performance, forecast resource requirements, evaluate alternative allocation scenarios, and select resource configurations that are more closely aligned with institutional priorities. For socially impactful U.S. sectors, this type of platform is particularly relevant because many organizations must simultaneously manage cost pressures and service responsibilities. Healthcare organizations must allocate staff, facilities, equipment, and budgets; educational institutions must coordinate instructors, technology, learning resources, and institutional expenditures; utilities must manage capacity, infrastructure, and demand; and public or nonprofit organizations must distribute limited funding across programs, populations, and service areas. These challenges demonstrate that resource optimization cannot be treated as a purely financial exercise. It requires coordinated consideration of demand, availability, utilization, cost, capacity, operational constraints, and service requirements. The present study therefore focuses on the design of an Economic Decision Intelligence Platform that brings together Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence as interconnected capabilities for improving Resource Optimization Performance in socially impactful U.S. sectors.

Problem Statement

Socially impactful organizations in the United States manage substantial economic and operational resources while facing persistent challenges related to limited budgets, increasing service demands, fragmented data environments, workforce shortages, infrastructure constraints, inefficient resource utilization, and pressure to demonstrate measurable organizational performance. A central problem is that resource decisions are frequently made through separate departmental systems or conventional reporting processes that do not fully integrate financial, operational, workforce, demand, asset, and service information. When data remain distributed across different systems, decision-makers may lack a complete view of resource availability, current utilization levels, anticipated demand, operational constraints, and the economic consequences of alternative allocation choices. This fragmentation can contribute to delayed decisions, duplication of resources, underutilized capacity, excessive costs, inaccurate forecasting, inefficient staffing, poor coordination, and resource allocation that does not adequately reflect organizational priorities. Another problem concerns the limited integration of predictive and optimization capabilities within existing decision-support environments. Organizations may possess descriptive dashboards and reporting tools that explain historical conditions, yet such systems may provide insufficient support for predicting emerging resource requirements or identifying the most efficient allocation among competing alternatives. Artificial intelligence and advanced analytics can potentially address these limitations, but their usefulness depends on how effectively they are incorporated into organizational decision processes. An isolated predictive model cannot optimize resources if its outputs are disconnected from operational constraints, and an optimization algorithm cannot provide dependable recommendations if the underlying economic and organizational data are incomplete or inconsistent. Real-time decision support is also required because changes in demand, capacity, service conditions, and resource availability can alter the appropriateness of previously selected allocations. The research problem is therefore not merely the absence of data or analytical technologies, but the lack of an integrated economic decision intelligence structure that connects data integration, prediction, AI-based resource optimization, and real-time decision support with measurable Resource Optimization Performance. Existing organizational practices may employ some of these capabilities independently, yet their combined influence on resource optimization across socially impactful U.S. sectors requires systematic quantitative examination. This study addresses this problem by empirically evaluating the relationships between four Economic Decision Intelligence capabilities and Resource Optimization Performance and by using the resulting statistical evidence to support the design of an integrated platform suitable for selected socially impactful organizational environments.

Purpose and Objectives of the Study

The primary purpose of this study is to design and empirically evaluate an Economic Decision Intelligence Platform for improving resource optimization within socially impactful U.S. sectors through the coordinated use of integrated organizational data, predictive economic analytics, artificial intelligence, optimization techniques, and real-time decision support. The study has been structured around a set of interconnected objectives that translate this broader purpose into measurable empirical relationships. The first objective is to assess the level of Integrated Economic Data Intelligence within the selected organizations and determine whether decision-makers have sufficient access to coordinated financial, operational, workforce, asset, demand, and service-related information for resource planning. The second objective is to examine the relationship between Integrated Economic Data Intelligence and Resource Optimization Performance in order to determine whether stronger information integration is associated with improved utilization, allocation accuracy, capacity coordination, and cost control. The third objective is to evaluate the effect of Predictive Economic Analytics on Resource Optimization Performance by examining the extent to which forecasting, statistical analysis, machine learning, scenario evaluation, and predictive models contribute to the anticipation of resource needs and economic conditions. The fourth objective is to determine the influence of AI-Driven Resource Allocation and Optimization on Resource Optimization Performance by assessing whether algorithm-supported decision processes can improve the selection and distribution of limited organizational resources under operational and economic constraints. The fifth objective is to evaluate the effect of Real-Time Decision Support Intelligence on Resource Optimization Performance, particularly the role of timely information, automated alerts, analytical dashboards, scenario information, and updated decision recommendations in supporting adjustments to resource allocation. The sixth objective is to determine the combined predictive contribution of all four Economic Decision Intelligence dimensions to Resource Optimization Performance through multiple regression analysis. The final objective is to use the empirical results to develop a statistically supported Economic Decision Intelligence Platform that reflects the relative importance of the examined capabilities. Together, these objectives provide a direct connection between the conceptual platform and the quantitative research design, allowing descriptive statistics, correlation analysis, and regression modeling to evaluate both individual relationships and the overall explanatory structure of the proposed model.

Research Hypotheses

The research hypotheses have been formulated to provide statistically testable statements concerning the relationships between the major dimensions of the proposed Economic Decision Intelligence Platform and Resource Optimization Performance. The first hypothesis, H1, states that Integrated Economic Data Intelligence has a statistically significant positive effect on Resource Optimization Performance. This hypothesis reflects the expectation that organizations capable of combining financial, operational, workforce, demand, asset, and service information within a coherent analytical environment will be better positioned to allocate and utilize resources efficiently. The second hypothesis, H2, states that Predictive Economic Analytics has a statistically significant positive effect on Resource Optimization Performance. This hypothesis is based on the expectation that organizations using predictive models, statistical analysis, forecasting, and scenario-based assessment will be better able to anticipate resource requirements, demand changes, economic pressures, and capacity constraints. The third hypothesis, H3, proposes that AI-Driven Resource Allocation and Optimization has a statistically significant positive effect on Resource Optimization Performance. This relationship assumes that artificial intelligence and optimization mechanisms can assist decision-makers in comparing alternative resource configurations and identifying combinations that more effectively satisfy organizational objectives and constraints. The fourth hypothesis, H4, states that Real-Time Decision Support Intelligence has a statistically significant positive effect on Resource Optimization Performance. This hypothesis reflects the expectation that timely dashboards, alerts, current performance information, and updated analytical recommendations can improve resource adjustments when operating conditions change. The fifth hypothesis, H5, states that Economic Decision Intelligence capabilities collectively have a statistically significant positive effect on Resource Optimization Performance. This combined hypothesis recognizes that the proposed platform is designed as an integrated decision system rather than a collection of unrelated technological components. Statistical testing of these hypotheses has therefore examined both individual and collective relationships among the study variables. Pearson correlation analysis has determined the strength and direction of the associations between each Economic Decision Intelligence dimension and Resource Optimization Performance, while multiple regression analysis has determined the independent contribution of each predictor after the effects of the other variables have been considered. The overall regression model has also established whether the four dimensions collectively explain a statistically significant proportion of variation in Resource Optimization Performance within the selected socially impactful U.S. organizations.

Significance of the Research

i. Significance to Organizational Decision-Makers: The study is significant to managers and senior decision-makers because it provides a structured approach for understanding how integrated data, predictive analysis, artificial intelligence, optimization, and real-time information can be organized within a single decision architecture. The proposed platform can help decision-makers examine resource conditions more systematically and identify which analytical capabilities have the strongest relationship with Resource Optimization Performance.

ii. Significance to Socially Impactful U.S. Sectors: The research is particularly relevant to healthcare, education, public utilities, infrastructure, social services, energy, and other sectors in which resource decisions directly affect organizational capacity and service delivery. By focusing on these environments, the study addresses resource management in settings where financial efficiency must operate alongside operational and service requirements.

iii. Significance to Resource Planning and Operations Professionals: Professionals involved in budgeting, workforce planning, capacity management, procurement, service allocation, asset utilization, and operational planning may use the study framework to understand how data-driven and AI-supported decision capabilities can be connected with routine resource-management processes.

iv. Significance to Information Systems and Analytics Professionals: The study provides a multidimensional representation of decision intelligence that moves beyond isolated dashboards, predictive models, or optimization systems. It identifies the need to connect data integration, prediction, algorithmic optimization, and real-time decision support so that analytical outputs can be translated into organizational resource decisions.

v. Significance to Policymakers and Public Administrators: For public and socially oriented organizations, the research offers a framework for evaluating how advanced analytical technologies may be incorporated into administrative decision processes while maintaining human oversight and organizational accountability. The model can assist in identifying the technological and managerial capabilities required for evidence-based resource allocation.

vi. Significance to Academic Research: The study contributes to scholarship by operationalizing Economic Decision Intelligence as a measurable organizational construct composed of four distinct but related dimensions. It also connects these dimensions with Resource Optimization Performance through a quantitative, cross-sectional, case-study-based design. The resulting statistical model provides a foundation for examining decision intelligence through descriptive analysis, correlation analysis, and multiple regression rather than treating it only as a conceptual or technological phenomenon.

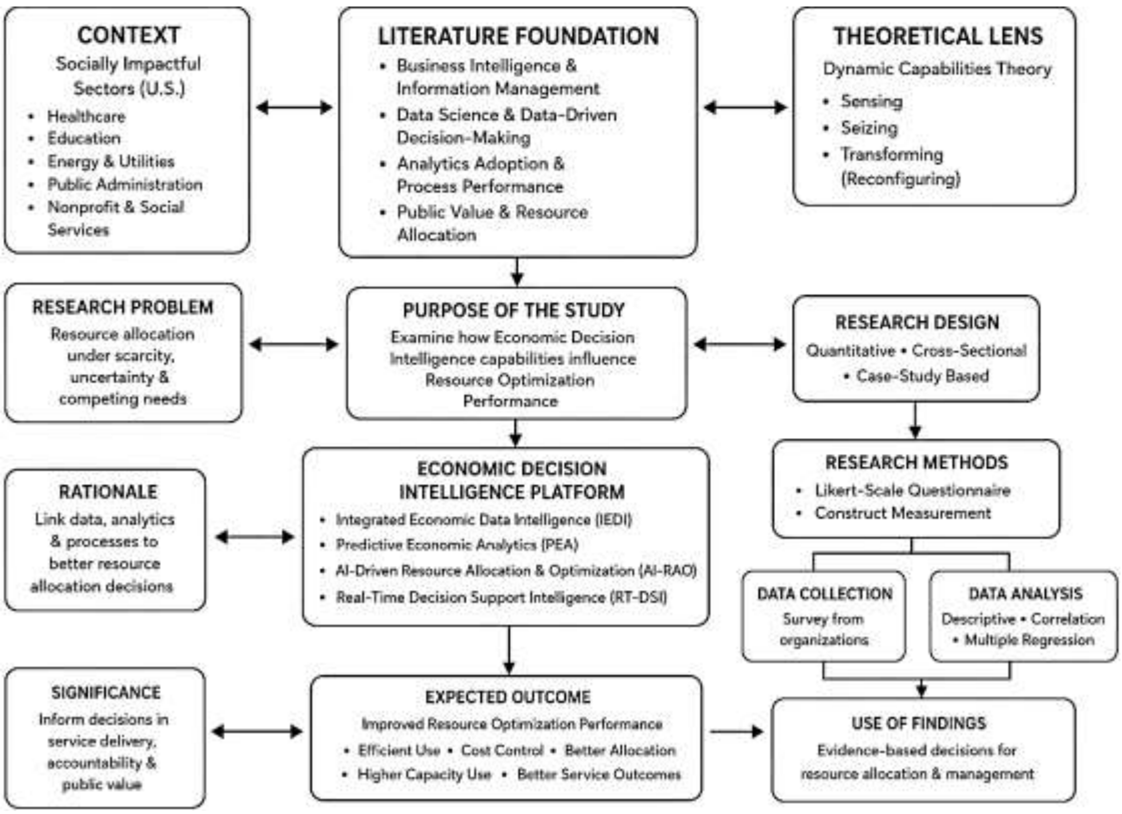
LITERATURE REVIEW

The literature surrounding economic decision intelligence, artificial intelligence, analytics, and resource optimization spans several interconnected research domains, including decision support systems, business intelligence, big-data analytics, predictive modeling, operations research, artificial intelligence, public-sector digitalization, organizational capabilities, and resource-management theory. A systematic examination of these areas is necessary because the proposed Economic Decision Intelligence Platform does not represent a single technology or analytical technique. Instead, it represents an integrated organizational capability through which multiple categories of data are combined, analyzed, converted into predictions, used to evaluate alternative resource configurations, and delivered to decision-makers through timely decision-support mechanisms. The literature review therefore examines the technological, analytical, organizational, and theoretical foundations that support the relationship between decision intelligence and Resource Optimization Performance. Particular attention is given to socially impactful sectors because resource allocation within healthcare, education, utilities, infrastructure, public administration, and related organizations involves complex decisions concerning budgets, personnel, physical assets, technological resources, capacity, demand, and service requirements. The review first examines Economic Decision Intelligence and data-driven organizational decision-making to establish the conceptual foundations of technology-supported managerial decisions. It then evaluates Integrated Economic Data Intelligence and the role of data quality, interoperability, organizational information integration, and analytical accessibility in supporting resource planning. Predictive Economic Analytics is subsequently examined as a mechanism for forecasting demand, costs, risks, resource requirements, and operational conditions. The review also considers AI-Driven Resource Allocation and Optimization, emphasizing the use of artificial intelligence, machine learning, operations research, and optimization methods in selecting resource configurations under multiple organizational constraints. Real-Time Decision Support Intelligence is examined in relation to timely information, analytical dashboards, adaptive decision processes, and organizational responsiveness. Dynamic Capabilities Theory provides the principal theoretical framework for explaining how organizations can sense changing conditions, seize appropriate responses, and reconfigure available resources through decision intelligence capabilities. The literature review finally develops the conceptual framework connecting Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence with Resource Optimization Performance, thereby establishing the analytical foundation for the hypotheses and empirical model tested in the study.

Economic Decision Intelligence and Data-Driven Decision-Making in Socially Impactful Sectors

Economic Decision Intelligence and data-driven decision-making represent a convergence of information systems, analytics, and structured decision processes through which institutions use data to guide choices concerning operations, finance, service delivery, and resource allocation. Within socially impactful sectors, this convergence is especially important because decisions influence service capacity, institutional accountability, and the distribution of scarce organizational resources. The development of business intelligence systems established an important foundation for this form of decision-making by enabling organizations to transform information stored in enterprise systems into analytical outputs that support managerial evaluation. Research examining business intelligence systems demonstrated that their value is most appropriately understood through changes in business-process performance and organizational performance rather than technology acquisition alone, and it also showed that the strength of these relationships can vary across industry contexts (Elbashir et al., 2008). This process-oriented perspective is directly relevant to Economic Decision Intelligence because an integrated platform must connect analytical information with the decisions and operational processes through which resources are actually deployed. Information management capability provides another essential foundation. Organizations require mechanisms for gathering, organizing, accessing, interpreting, and distributing information before analytical outputs can consistently influence resource decisions. Evidence has shown that IT-enabled information management capability contributes to the development of customer-management, process-management, and performance-management capabilities, which in turn are associated with financial, human-resource, and organizational effectiveness outcomes (Mithas et al., 2011). In socially impactful U.S. sectors, these relationships can be interpreted through the need to coordinate multiple forms of economic and operational information before managers determine how budgets, personnel, facilities, infrastructure, technologies, or service capacity should be allocated. Economic Decision Intelligence therefore extends conventional reporting by creating a structured connection between data availability, analytical interpretation, organizational processes, and decision execution, allowing evidence to become an active component of resource-management practice rather than a passive record of previous activity.

Figure 2: Economic Decision Intelligence Platform for Resource Optimization in Socially Impactful Sectors



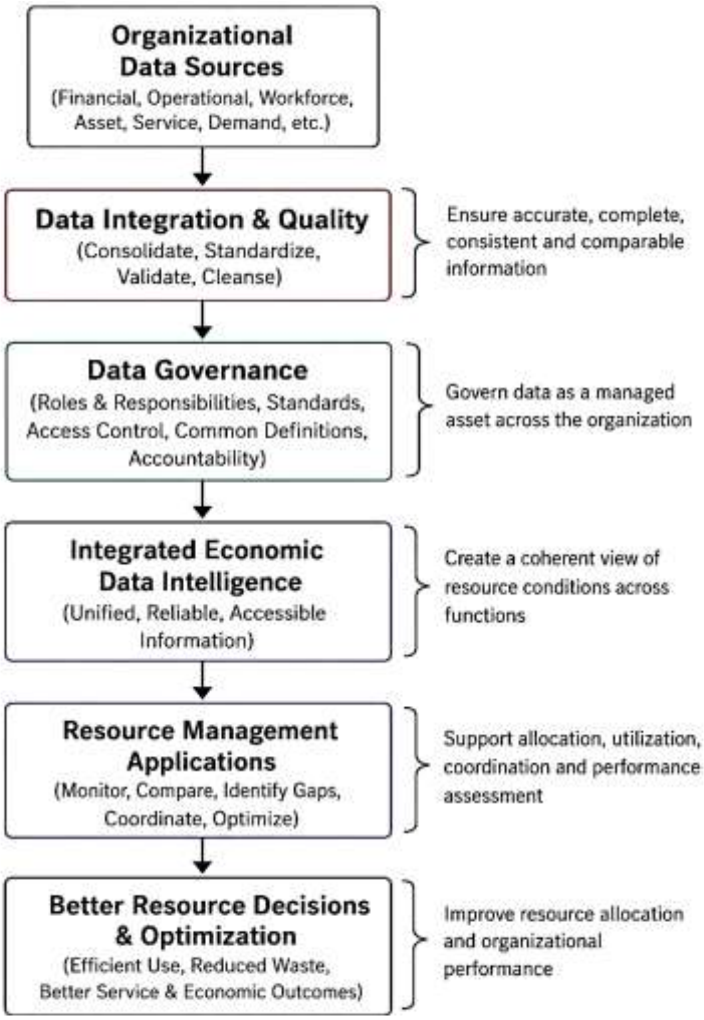
Data-driven decision-making further develops this perspective by shifting organizational choices from dependence on intuition or retrospective reporting toward systematic empirical analysis. The central principle is not that human judgment is removed from decision processes, but that relevant data are deliberately incorporated into problem identification, comparison of alternatives, estimation of outcomes, and selection of actions. Data science provides a methodological bridge between raw data and such decisions because its analytical principles and techniques enable organizations to extract patterns and predictive knowledge from information environments. Data-driven decision-making has consequently been described as the practice of basing decisions on data analysis rather than relying purely on intuition, while recognizing that organizations may combine analytical evidence with managerial expertise to varying degrees (Provost & Fawcett, 2013). This distinction is important for socially impactful sectors because resource decisions combine economic variables with institutional priorities. A hospital administrator may evaluate demand, staffing, treatment capacity, and cost data; an educational administrator may examine enrollment, faculty workload, and expenditure; and a utility manager may consider demand, infrastructure capacity, asset condition, and operating cost. Across these environments, analytical value depends on whether information can be converted into improved organizational processes. Empirical work on business analytics has shown that analytics adoption can positively influence business-process performance and that improved process performance can mediate the relationship between analytics adoption and broader firm performance (Aydiner et al., 2019). This finding reinforces the logic of an Economic Decision Intelligence Platform because advanced analytics should not be treated as an isolated technical layer. Predictive models, optimization procedures, dashboards, and integrated databases become meaningful when their outputs alter planning, coordination, prioritization, and allocation processes. Data-driven decision-making in this sense represents an organizational discipline in which data quality, analytical capability, managerial interpretation, and process execution operate together to produce more systematic choices concerning scarce resources consistently.

The relevance of Economic Decision Intelligence becomes more pronounced when decision-making concerns public value and socially consequential resource distribution. Socially impactful organizations often operate where available resources are insufficient to satisfy every competing need simultaneously, requiring managers and administrators to determine which activities, facilities, programs, or service areas should receive priority. These decisions are complicated by uncertainty because demand, costs, capacity, service requirements, and environmental conditions may change while decision-makers possess incomplete information about the consequences of alternative allocations. Data-driven approaches can structure this uncertainty by combining evidence with models that compare alternative actions. In public-health resource allocation, a robust data-driven decision approach was used to compare intervention strategies across numerous simulated scenarios for HIV/AIDS care and prevention in Los Angeles County. The analysis demonstrated how decision tools could help public agencies evaluate alternative uses of scarce resources against defined policy objectives rather than relying only on prevailing allocation patterns (Ryan et al., 2014). This application reflects the present study's central principle: decision intelligence should connect evidence with resource choices in environments where both economic efficiency and service outcomes matter. For socially impactful U.S. sectors, an Economic Decision Intelligence Platform can be conceptualized as an organizational decision architecture that combines integrated economic data, analytical processing, predictive assessment, optimization, and timely decision support. Its role is to organize information around resource questions such as what resources are available, where they are currently used, what demand is expected, which constraints are binding, what alternative allocations are feasible, and how different choices may affect organizational performance. The literature on data-driven decision-making thus provides the conceptual basis for treating Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence as coordinated capabilities that can be examined in relation to Resource Optimization Performance across diverse organizational settings effectively.

Integrated Economic Data Intelligence and Organizational Resource Management

Integrated Economic Data Intelligence refers to an organization's capability to consolidate, standardize, govern, and interpret economic, financial, operational, workforce, asset, service, and demand-related data so that decision-makers can obtain a coherent representation of resource conditions across organizational functions. This capability occupies an important position within resource management because effective allocation decisions depend on the accuracy, completeness, consistency, accessibility, and comparability of the information used to evaluate available resources and competing organizational requirements. In complex organizations, relevant information may originate from financial management systems, human-resource databases, enterprise resource planning platforms, service-management applications, asset records, procurement systems, customer or citizen databases, and operational monitoring technologies. When these sources are poorly integrated, managers may encounter conflicting values, duplicated records, incomplete information, inconsistent classifications, and delayed access to important economic indicators. Data quality management therefore represents a fundamental requirement for integrated decision intelligence. A systematic examination of data-quality methodologies demonstrated that organizations can improve data through both data-driven approaches, which directly modify or correct information, and process-driven approaches, which redesign the organizational activities responsible for generating or maintaining data (Batini et al., 2009). This distinction is important for resource management because inaccurate resource information cannot always be corrected solely through technological intervention; the underlying organizational processes producing such information must also be controlled. Data governance strengthens this process by defining roles, responsibilities, decision rights, and accountability for organizational data. Research examining governance arrangements across international organizations has demonstrated that data-governance structures must account for organizational characteristics such as strategy, structure, regulation, process harmonization, and decision-making style rather than following a universal governance configuration (Weber et al., 2009). For socially impactful U.S. sectors, Integrated Economic Data Intelligence therefore requires both technological integration and institutional coordination so that information concerning budgets, workforce capacity, infrastructure, demand, service utilization, and operational performance can be managed as interconnected organizational resources.

Figure 3: Integrated Economic Data Intelligence Framework for Organizational Resource Management



The organizational usefulness of integrated economic data also depends on clearly established governance mechanisms that determine who owns particular information, who may access or modify it, how quality standards are established, and how data definitions are coordinated across departments (Debasish, 2021; Md. Abdur & Iftekhar, 2021). Data integration without governance may create a technically centralized environment while retaining ambiguity over authority, accountability, standards, and decision rights. This problem is particularly relevant when financial, human-resource, operational, and service information originate from different organizational units with separate objectives and reporting practices (Md Ashfaq & Abdullah Mohammad, 2022; Md Asif Ali Sheak & Risha, 2022). A structured approach to data governance distinguishes several important decision domains, including principles for organizational data, quality requirements, metadata arrangements, data access, and lifecycle responsibilities, thereby helping organizations treat information as a managed asset rather than an incidental output of operational systems (Khatri & Brown, 2010). Such governance mechanisms are directly connected to resource optimization because managers require common definitions and reliable information when comparing utilization across facilities, departments, programs, or service categories. If one organizational unit measures capacity, expenditure, staffing requirements, or service demand differently from another, aggregated analysis may produce misleading resource comparisons. Integrated Economic Data Intelligence must consequently incorporate common data definitions, controlled access, documented responsibilities, validation procedures, interoperability, and mechanisms for resolving inconsistencies (Mohammad Abir Chowdhury & Tonay, 2022; Nishat & Mst Kaniz, 2022). A comprehensive review of data-governance scholarship identified governance mechanisms, organizational scope, data scope, domain scope, antecedents, and consequences as central elements for understanding how organizations exercise authority and control over data resources (Abraham et al., 2019). This broader view is highly applicable to socially impactful sectors because resource-management decisions frequently cross organizational boundaries. Healthcare systems may integrate clinical, financial, staffing, and capacity data; educational institutions may combine enrollment, expenditure, staffing, facilities, and performance information; while public-service and infrastructure organizations may connect budgetary, geographic, asset, demand, and service records. Integrated Economic Data Intelligence therefore provides the informational foundation through which these heterogeneous sources can be transformed into a unified representation of organizational resource conditions and made available for systematic economic decision-making (Abdullah Mohammad, 2023; Shaiful et al., 2022).

The connection between Integrated Economic Data Intelligence and organizational resource management becomes strongest when governed information is transformed into evidence that supports resource allocation, monitoring, coordination, and performance assessment. Resource management involves determining what resources exist, where they are located, how intensively they are utilized, what costs they generate, which organizational activities require additional capacity, and where inefficiency or underutilization occurs (Mohammad Abir Chowdhury, 2023; Mohammad Badrul & Md. Mominul, 2023). These questions cannot be answered reliably when managers operate with incomplete, outdated, inconsistent, or departmentally isolated information. An integrated intelligence environment can instead create common visibility across financial resources, workforce availability, service requirements, physical assets, procurement commitments, operating capacity, and organizational performance measures (Ashrafuzzaman, 2024; Muhammad Zahidul, 2023). Such visibility allows managers to compare resource demand with resource availability, identify areas of excessive expenditure or unused capacity, coordinate activities across organizational units, and establish more consistent bases for allocation decisions. Information governance is especially relevant to this process because the quality of analytical output depends on the organizational structures and processes through which information is managed (Kazi Rakib Hasan, 2024; Md Anisur Rahman, 2024). Empirical evidence from managers has shown that dimensions of information governance relating to organizational strategy and processes can improve information quality, while collaboration between information technology and functional decision-makers can strengthen the relationship between governance activities and information outcomes (Sleep et al., 2024). Within the proposed Economic Decision Intelligence Platform, Integrated Economic Data Intelligence therefore functions as more than a data-aggregation mechanism. It establishes the controlled informational environment upon which Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time

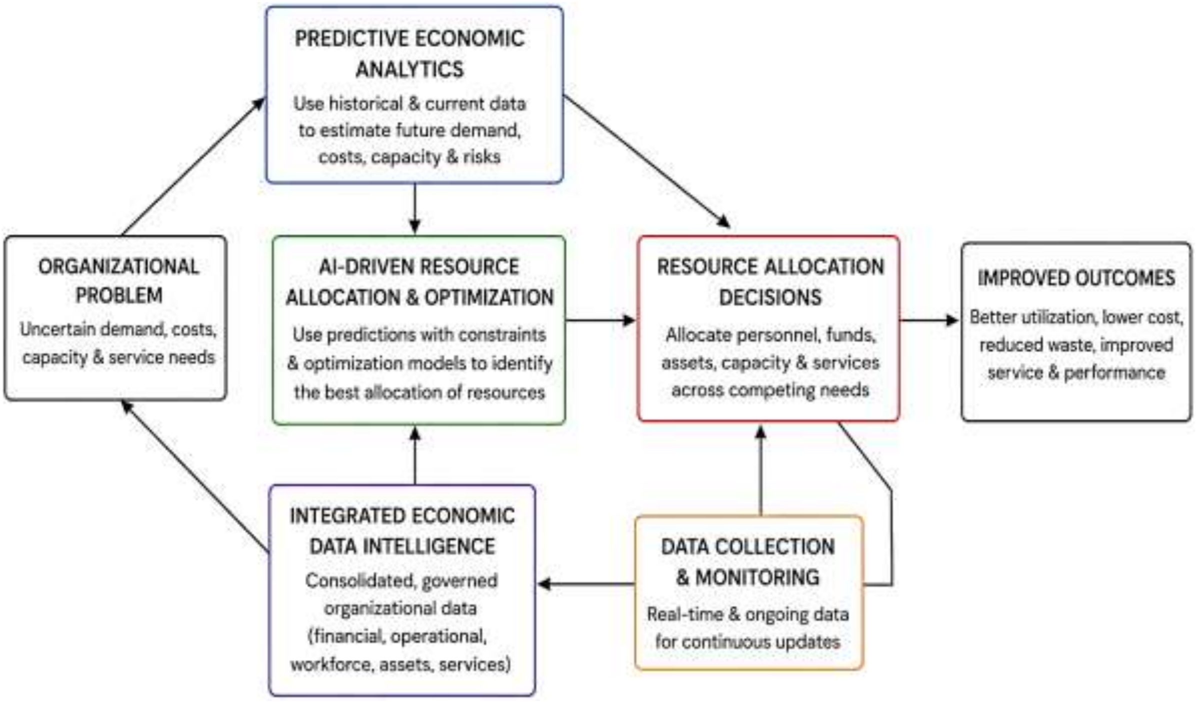
Decision Support Intelligence depend (Md Asif Ali Sheak, 2024; Nishat & Jahanara, 2024). Predictive models require consistent historical data, optimization algorithms require reliable descriptions of resource constraints and availability, and real-time decision systems require current and interoperable information flows. Within socially impactful U.S. organizations, these requirements are especially significant because resource-management errors can influence both economic performance and institutional service capacity (Debasish, 2025; Tonay et al., 2024). Integrated Economic Data Intelligence can consequently be conceptualized as the foundational capability that connects data quality, governance, interoperability, organizational accountability, and information accessibility with the broader process of resource optimization.

Predictive Economic Analytics and AI-Driven Resource Allocation

Predictive Economic Analytics represents the systematic use of historical and current economic, operational, financial, and service data to estimate likely future conditions and support more informed organizational decisions (Jannatul, 2025; Md Anisur Rahman, 2025). Within socially impactful sectors, predictive capability is important because managers must allocate resources before actual demand, costs, capacity requirements, or service pressures are fully known (Md Arif Uz et al., 2025; Md Mahamud Pervaz, 2025). Predictive analytics differs from purely descriptive analysis by emphasizing what is likely to occur rather than only summarizing what has already happened. It can incorporate regression analysis, classification, time-series forecasting, machine learning, probability models, and other computational techniques to identify patterns and estimate future outcomes (Mohammad Abir Chowdhury, 2025; Mohammad Badrul, 2025). A central methodological distinction is that predictive modeling focuses on out-of-sample predictive performance rather than assuming that explanatory statistical relationships will automatically generate accurate forecasts. This distinction has been emphasized in information-systems research, where predictive analysis has been identified as a separate analytical objective that can contribute practical value by testing whether models accurately estimate unseen outcomes (Shmueli & Koppius, 2011). In an Economic Decision Intelligence Platform, this orientation is essential because decisions concerning workforce levels, budget requirements, asset utilization, service capacity, inventory, infrastructure, and operational scheduling are frequently made before actual conditions become observable (Nishat, 2025; Nuzhat Sadia, 2025; Tonay, 2025). Predictive Economic Analytics can therefore transform integrated organizational data into estimates concerning resource demand, expenditure pressures, service volumes, capacity constraints, and operational risk. In supply-chain and logistics contexts, data science and predictive analytics have been recognized as important tools for improving forecasting and decision-making by combining domain knowledge with quantitative techniques capable of extracting useful signals from large datasets (Waller & Fawcett, 2013). Socially impactful U.S. sectors also manage interconnected flows of people, funds, equipment, facilities, and services. Predictive Economic Analytics consequently provides an analytical bridge between integrated data and resource-allocation decisions by converting observations into estimates that guide planning before shortages, excess capacity, or inefficient spending become operational problems.

The value of predictive analysis becomes greater when forecasts are directly connected to resource-allocation and optimization processes. A forecast informs decision-makers about an expected condition, but it does not necessarily determine which combination of resources should be selected under budgetary, operational, capacity, or service constraints. AI-Driven Resource Allocation and Optimization therefore represents the use of machine-learning outputs, optimization algorithms, decision rules, and computational models to identify resource configurations that better satisfy organizational objectives. This relationship between prediction and optimization can be observed where demand forecasts are translated into operational decisions. Research involving an online retailer combined machine-learning-based demand forecasting with a multiproduct price-optimization algorithm and incorporated the resulting model into a practical decision-support tool used for daily pricing decisions (Ferreira et al., 2016). The importance of this example lies in the analytical sequence: historical data are processed, future demand is estimated, constraints and decision alternatives are represented, and an optimization mechanism converts predictions into recommended actions. A similar structure can be applied to socially impactful sectors. Healthcare organizations can estimate patient demand and use those estimates to guide staffing or capacity decisions; educational institutions can estimate enrollment and align faculty, facilities, and support resources; utilities can forecast consumption and coordinate infrastructure capacity; and public-service organizations can estimate program demand and allocate financial or operational resources accordingly. Operations-management research has demonstrated that big-data analytics can support forecasting, inventory management, revenue management, transportation, supply-chain coordination, and risk analysis, while data-driven optimization converts operational data into actionable decisions (Choi et al., 2018). Within the proposed Economic Decision Intelligence Platform, AI-Driven Resource Allocation and Optimization functions as the action-oriented component that follows prediction. It evaluates feasible alternatives according to organizational goals and constraints, allowing predicted resource requirements to be translated into decisions concerning how limited assets, funds, personnel, infrastructure, or service capacity should be distributed across competing needs.

Figure 4: Predictive Economic Analytics and AI-Driven Resource Allocation Framework



The integration of prediction and AI-supported optimization is especially significant when organizations operate under uncertainty and must balance economic efficiency with service requirements. Socially impactful U.S. organizations frequently confront situations in which under-allocation can reduce service capacity while over-allocation can create waste, unnecessary cost, idle resources, or inefficient deployment. The quality of a resource decision therefore depends on both the accuracy of information used to anticipate demand and the suitability of the method used to transform that information into an allocation (Jannatul, 2026; Md Anisur Rahman, 2026). Data-driven optimization can strengthen this connection by using observable features and historical outcomes directly within decision models. An important example is the data-driven newsvendor framework developed for decisions under uncertain demand, in which machine-learning methods were used to determine decision quantities from feature-rich historical data rather than relying exclusively on separately estimated demand distributions (Md Mahamud Pervaz, 2026; Mohammad Abir Chowdhury, 2026). When the framework was applied to nurse staffing in a hospital emergency department, the strongest feature-based algorithms produced lower out-of-sample costs than the benchmark approach, illustrating how prediction and optimization can be combined within a socially consequential resource-allocation setting (Ban & Rudin, 2019). The relevance of this evidence to the present study is that AI-supported resource optimization should not be treated as an abstract technological capability. It can be operationalized as the organizational capacity to evaluate complex data, anticipate resource requirements, incorporate economic and service constraints, compare alternative allocations, and recommend decisions that improve utilization and reduce avoidable inefficiency (Mohammad Badrul, 2026; Nishat, 2026). Within an Economic Decision Intelligence Platform, Predictive Economic Analytics and AI-Driven Resource Allocation and Optimization are closely connected but analytically distinct. Predictive analytics estimates what conditions are likely to occur, while optimization determines how available resources should be configured in response to those estimates. Their coordinated use can support proactive resource planning, improved matching of supply with demand, stronger capacity utilization, reduced unnecessary expenditure, and more consistent decision processes across socially impactful U.S. sectors.

Real-Time Decision Support Intelligence and Resource Optimization Performance

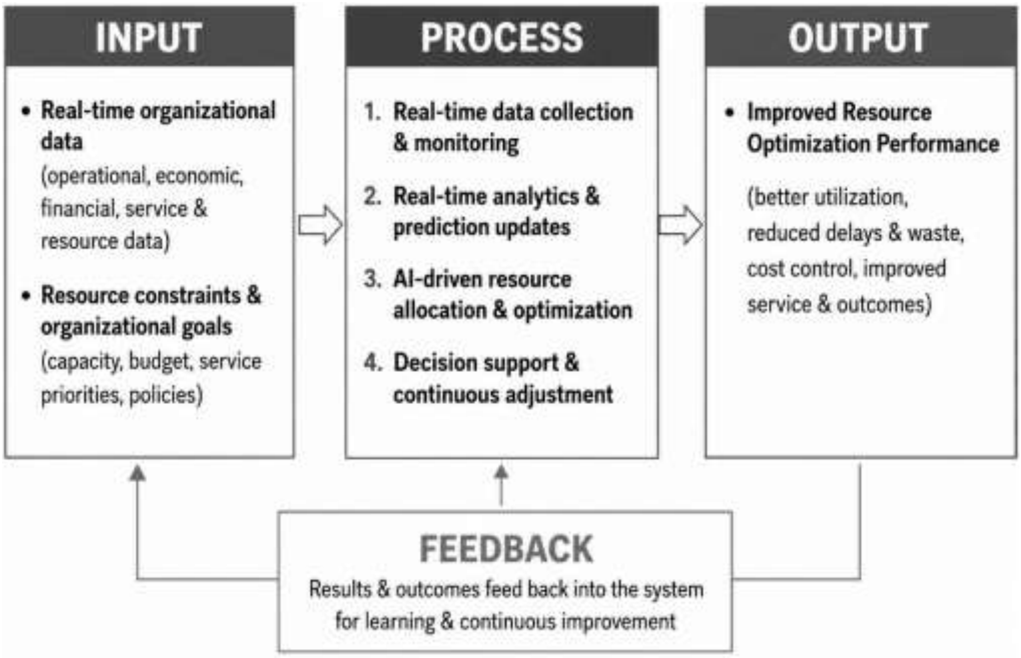
Real-Time Decision Support Intelligence refers to an organizational capability through which operational, economic, financial, service, and resource information is transformed into decision-relevant outputs at the point when managers need to act. The concept differs from conventional reporting because the value of information is determined not only by accuracy and completeness but also by the degree to which data latency is reduced and analytical outputs are synchronized with ongoing organizational conditions (Nuzhat Sadia, 2026; Rony & Md, 2026). In resource-intensive settings, delayed information can cause managers to allocate personnel, funds, equipment, capacity, or inventory on the basis of conditions that have already changed. Real-time business intelligence therefore seeks to shorten the interval between data generation, analytical processing, managerial interpretation, and response (Tonay, 2026). Research on real-time business intelligence has shown that reduced data latency can improve access to current information while supporting planning environments that contain changing supply, demand, capacity, inventory, and production conditions (Rutz et al., 2012). This connection is directly relevant to an Economic Decision Intelligence Platform because resource optimization depends on the ability to compare available capacity with actual or emerging requirements before inefficiencies become embedded in operational processes. Real-time intelligence also extends beyond dashboards by supporting dynamic rather than exclusively forecast-driven resource decisions. Relational model-based approaches have demonstrated how organizations can use continually refreshed information to support operational decision-making and move from static, post hoc analysis toward more dynamic allocation of resources (Baker, 2013). Within socially impactful U.S. sectors, this capability may involve continuously updated indicators of staffing, service demand, budget consumption, facility capacity, asset availability, procurement status, infrastructure load, or program utilization. Real-Time Decision Support Intelligence can consequently be conceptualized as the mechanism that connects changing organizational conditions with managerial action, ensuring that decision-makers receive current evidence to reconsider priorities, compare alternatives, and adjust resource allocations when the operational environment no longer matches earlier assumptions.

The relationship between real-time decision support and Resource Optimization Performance becomes visible in socially impactful environments where delays in resource allocation can reduce service coverage, increase response times, raise operating costs, or leave critical capacity unused. Healthcare emergency systems provide a strong example because the location and availability of ambulances, personnel, treatment facilities, and resources change while demand is uncertain and geographically distributed. A model-driven real-time decision support system for ambulance relocation has shown that updated demand categories, ambulance locations, coverage conditions, workload limitations, and relocation costs can be incorporated into allocation decisions. The system was designed to maximize demand coverage while minimizing travel time and demonstrated improvements in response time and coverage relative to existing policy (Hajiali et al., 2022). Such evidence illustrates the central logic of real-time resource optimization: decisions should be recalculated when system conditions change rather than remaining fixed according to earlier schedules or static assumptions. The same principle applies to the distribution of scarce public-health resources. A decision support system developed for prioritized COVID-19 vaccine allocation integrated geographic information, analytics, simulation, supply scenarios, capacity constraints, and vulnerability criteria to support allocation decisions under time-sensitive conditions. The framework enabled planners to adjust distribution plans in response to disruptions while prioritizing vulnerable populations and reducing logistical resource requirements

(Shahparvari et al., 2022). These applications are relevant because socially impactful U.S. organizations operate under conditions of limited resources, competing priorities, variable demand, and service obligations. Real-Time Decision Support Intelligence can support Resource Optimization Performance by enabling organizations to monitor resource positions, identify shortages or excess capacity, respond to changing demand, revise allocations, and reduce delays between recognizing a resource problem and implementing corrective action. Real-time intelligence is therefore an operational capability through which timely data, analytical models, resource constraints, and decision rules support continuous adjustment of organizational resources.

Another dimension of Real-Time Decision Support Intelligence concerns the quality of interaction between analytical systems and human decision-makers. Resource optimization in socially impactful sectors cannot depend entirely on automated recommendations because allocation decisions may involve service priorities, safety requirements, regulatory rules, budget constraints, workload considerations, and contextual information that may not be fully represented algorithmically. Real-time decision support must therefore allow decision-makers to understand current conditions, evaluate recommended actions, compare alternative responses, and retain appropriate control over consequential decisions. Research in safety-critical railway control rooms has demonstrated this human-centered approach through a real-time decision support system that combined machine-learning predictions, explanations, and behavioral prescriptions for railway traffic management. The system was designed to provide proactive support on automation use while communicating agreement levels across different modeling approaches and incorporating end-user feedback on operational use (Sobrie & Verschelde, 2024).

Figure 5: Real-Time Decision Support Intelligence Framework for Resource Optimization Performance



This design is relevant to an Economic Decision Intelligence Platform because timely recommendations become more useful when managers can interpret their analytical basis and connect them with organizational priorities. Resource Optimization Performance can therefore be viewed as an outcome of computational capability and decision responsiveness. A real-time system may increase data-processing speed, but organizational performance depends on whether the resulting information supports better allocation accuracy, capacity utilization, waste reduction, cost control, resource-demand matching, and coordinated deployment of organizational assets. Within the conceptual model, Real-Time Decision Support Intelligence represents the fourth explanatory capability following Integrated Economic Data Intelligence, Predictive Economic Analytics, and AI-Driven Resource Allocation and Optimization. Integrated data establish visibility, predictive analytics estimate likely conditions, AI-supported optimization evaluates feasible resource configurations, and real-time decision support delivers current analytical guidance as conditions evolve. The literature therefore supports treating Real-Time Decision Support Intelligence as a distinct measurable construct whose relationship with Resource Optimization Performance can be tested quantitatively across selected socially impactful U.S. sectors.

Theoretical Framework: Dynamic Capabilities Theory

Dynamic Capabilities Theory provides an appropriate theoretical foundation for explaining how an Economic Decision Intelligence Platform can influence Resource Optimization Performance in socially impactful U.S. sectors because the theory focuses on an organization's capacity to recognize changing conditions, mobilize appropriate responses, and reconfigure its resource base when existing routines no longer adequately match environmental or operational requirements. The theory is especially relevant to organizations operating in healthcare, education, public utilities, infrastructure, energy, and social-service environments, where managers must repeatedly adjust financial, human, technological, physical, and informational resources in response to variations in demand, service requirements, budget limitations, institutional priorities, and operational constraints. Dynamic capabilities should not be understood simply as ordinary routines used to perform current activities; they represent higher-order organizational capacities through which existing resources and operational capabilities can be modified, extended, coordinated, or renewed. The developmental perspective of dynamic capabilities emphasizes that such capabilities emerge, evolve, and change through organizational learning and repeated managerial action, which makes the framework particularly suitable for examining data-driven decision systems that alter how organizations identify, evaluate, and deploy resources (Helfat & Peteraf, 2009). Dynamic capabilities have also been conceptualized as a multidimensional organizational construct involving the propensity to identify opportunities and threats, make timely and strategically appropriate decisions, and modify the organizational resource base when changing circumstances require adaptation (Barreto, 2010). Within the present study, these theoretical functions are represented through four measurable dimensions of Economic Decision Intelligence. Integrated Economic Data Intelligence provides visibility into resource availability, utilization, economic conditions, and organizational constraints; Predictive Economic Analytics facilitates recognition of likely demand, cost, capacity, and risk conditions; AI-Driven Resource Allocation and Optimization assists in evaluating and reconfiguring resource combinations; and Real-Time Decision Support Intelligence enables organizational decision-makers to revise allocations when current operating conditions differ from previous assumptions. The theoretical relationship among these capabilities can therefore be represented as follows.

$$DC_i = f(IEDI_i, PEA_i, AI - RAO_i, RTDSI_i)$$

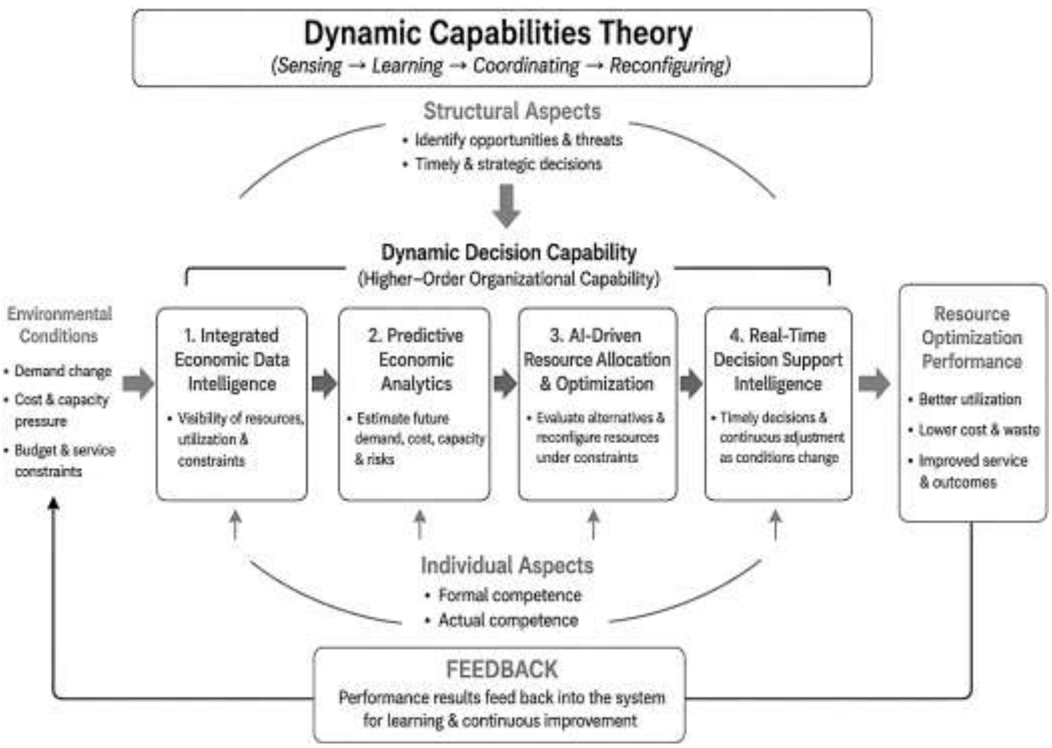
In this expression, DC represents the dynamic decision capability associated with an organizational case, while IEDI represents Integrated Economic Data Intelligence, PEA represents Predictive Economic Analytics, AI-RAO represents AI-Driven Resource Allocation and Optimization, and RTDSI represents Real-Time Decision Support Intelligence. These capabilities collectively describe the informational, predictive, optimization, and adaptive mechanisms through which the Economic Decision Intelligence Platform can support organizational resource reconfiguration.

The relevance of Dynamic Capabilities Theory to the present research becomes clearer when the internal mechanism linking decision intelligence with resource optimization is considered. An organization may possess extensive databases, analytical software, machine-learning models, dashboards, or artificial-intelligence technologies without necessarily achieving better resource outcomes if these assets are disconnected from organizational processes that sense changing conditions, interpret information, coordinate responses, and alter existing resource configurations. Empirical research has attempted to make dynamic capabilities measurable by identifying sensing, learning, coordinating, and integrating as important capabilities through which organizations reshape operational processes when environmental conditions change. Evidence from organizational units has demonstrated that dynamic capabilities can influence performance through the reconfiguration of existing operational capabilities and that this mechanism becomes particularly relevant under conditions characterized by substantial environmental turbulence (Pavlou & El Sawy, 2011). Within the proposed Economic Decision Intelligence Platform, Integrated Economic Data Intelligence and Predictive Economic Analytics primarily strengthen sensing and learning because they transform fragmented organizational information into current and anticipatory knowledge concerning demand, expenditure, resource utilization, operating capacity, and potential constraints. AI-Driven Resource Allocation and Optimization supports coordination and resource reconfiguration by evaluating alternative distributions of budgets, staff, facilities, technological systems, infrastructure, equipment, or service capacity according to defined economic and operational constraints. Real-Time Decision Support Intelligence completes this process by connecting analytical outputs with continuing managerial action so that resource allocations can be reconsidered when workloads, costs, demand levels, capacity requirements, or service conditions change. Because the present research uses a quantitative, cross-sectional design and evaluates explicit hypotheses, this theoretical relationship has been operationalized through a multiple regression model. The principal equation applied consistently throughout the methodology, hypothesis testing, results, and final empirical platform has been expressed as follows.

$$ROP_i = \beta_0 + \beta_1 IEDI_i + \beta_2 PEA_i + \beta_3 AI - RAO_i + \beta_4 RTDSI_i + \varepsilon_i$$

In the regression model, ROP represents Resource Optimization Performance, beta zero represents the regression intercept, beta one through beta four represent the effects of the four Economic Decision Intelligence capabilities, and epsilon represents unexplained variation. This equation is particularly suitable for the complete study because the standardized regression coefficients have determined the relative contribution of each capability, while the coefficient of determination has established the proportion of variation in Resource Optimization Performance collectively explained by the proposed Economic Decision Intelligence Platform.

Figure 6: Dynamic Capabilities Framework for Economic Decision Intelligence and Resource Optimization Performance



Dynamic Capabilities Theory also provides a foundation for explaining why the relationship between Economic Decision Intelligence capabilities and Resource Optimization Performance should be tested empirically rather than assumed to operate identically across organizations. The effectiveness of dynamic capabilities is connected to the organizational structures and environmental conditions within which they are deployed, meaning that similar analytical technologies may generate different performance outcomes when organizations differ in their capacity to absorb information, coordinate departments, modify routines, and translate analytical evidence into action. Empirical investigation has demonstrated that the performance effects of dynamic capabilities are influenced by organizational structure and competitive intensity, with internal alignment between organizational arrangements and dynamic capabilities playing an important role in determining organizational performance (Wilden et al., 2013). This perspective is highly relevant to socially impactful U.S. sectors because hospitals, educational institutions, energy organizations, public utilities, infrastructure organizations, and social-service providers differ substantially in their resource structures, demand conditions, regulatory environments, operating processes, technological maturity, and service priorities. Research has also demonstrated that the value generated through dynamic capabilities may vary according to environmental dynamism, indicating that their contribution to organizational advantage is contingent on the degree and nature of change confronting the organization rather than automatically increasing under every environmental condition (Schilke, 2014). The present study therefore does not assume that possessing sophisticated databases, predictive systems, artificial-intelligence applications, or real-time dashboards automatically creates Resource Optimization Performance. Instead, it examines whether the four Economic Decision Intelligence capabilities are statistically associated with the organization's ability to utilize available resources efficiently, improve allocation accuracy, control costs, reduce resource waste, strengthen capacity utilization, align resources with changing demand, and coordinate organizational assets. Under the proposed regression model, positive and statistically significant coefficients for the four predictors have provided empirical evidence that the corresponding Economic Decision Intelligence dimensions contribute positively to Resource Optimization Performance. The coefficient of determination has represented the proportion of observed variance in Resource Optimization Performance explained collectively by the four predictors, while the overall F-test has determined whether the regression model provides statistically significant explanatory power. The Dynamic Capabilities framework thus establishes a direct theoretical relationship between the organization's capacity to sense economic and operational conditions, analyze expected changes, select appropriate resource responses, reconfigure available assets, and achieve stronger resource optimization within the selected socially impactful U.S. sectors.

Conceptual Framework for the Economic Decision Intelligence Platform

The conceptual framework of this study establishes the proposed relationships between the major capabilities of an Economic Decision Intelligence Platform and Resource Optimization Performance within socially impactful U.S. sectors. A conceptual framework is particularly important for the present quantitative study because it translates the broader theoretical reasoning of Dynamic Capabilities Theory into specific measurable constructs that can be evaluated through descriptive statistics, correlation analysis, and multiple regression modeling. The framework identifies four independent variables, namely Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence, while Resource Optimization Performance represents the dependent variable. The first component captures the extent to which financial, operational, workforce, service, demand, and asset information is integrated and made accessible for organizational decision-making. Predictive Economic Analytics represents the ability to transform available information into forecasts concerning demand, cost, capacity, resource requirements, and operational conditions. AI-Driven Resource Allocation and Optimization reflects the organizational capability to use algorithmic analysis and optimization mechanisms to evaluate alternative resource configurations, while Real-Time Decision Support Intelligence captures the availability of timely analytical outputs, dashboards, alerts, and recommendations that assist managers in adjusting resource decisions as organizational conditions change. The conceptual logic is supported by evidence showing that business analytics can improve organizational decision-making effectiveness when analytical systems are aligned with appropriate information-processing requirements and organizational decision processes (Cao et al., 2015). Data analytics competency has also been shown to improve both decision quality and decision efficiency, particularly when organizations possess sufficient data quality, analytical skills, domain knowledge, and sophisticated analytical tools (Ghasemaghaei et al., 2018). These findings support the treatment of the four Economic Decision Intelligence dimensions as organizational capabilities rather than isolated technologies. Within the present framework, the dimensions are expected to operate independently and collectively because integrated information creates visibility, prediction transforms visibility into anticipated conditions, optimization evaluates feasible resource responses, and real-time intelligence supports timely managerial adjustment. The basic conceptual relationship has therefore been represented as follows.

$$EDI_{\mathrm{i}} = f(IEDI_{\mathrm{i}}, PEA_{\mathrm{i}}, AI - RAO_{\mathrm{i}}, RTDSI_{\mathrm{i}})$$

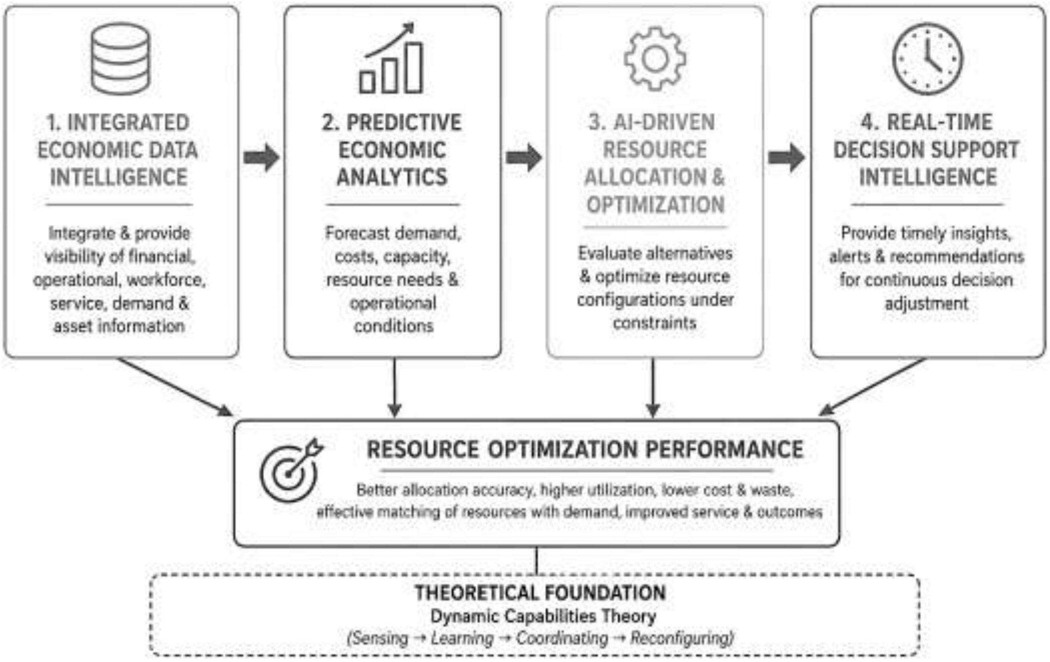
The dependent construct, Resource Optimization Performance, represents the extent to which an organization has been able to allocate and utilize its available resources efficiently while coordinating resource supply with organizational demand and operational requirements. Within socially impactful sectors, optimization cannot be represented only through reductions in expenditure because organizations must also maintain service capacity, workforce availability, infrastructure utilization, operational continuity, and appropriate distribution of resources across competing activities. Resource Optimization Performance has therefore been conceptualized through outcomes such as improved allocation accuracy, reduced unnecessary resource consumption, stronger capacity utilization, improved cost control, effective matching of resources with demand, reduced duplication, and more coordinated deployment of financial, human, physical, technological, and informational assets. The conceptual framework assumes that economic decision intelligence creates organizational value when analytical capabilities are translated into decisions and operational actions rather than when organizations simply acquire analytical technologies. A research framework examining strategic value from big-data analytics has similarly emphasized that analytical resources generate value through interconnected processes involving data, infrastructure, analytical capabilities, managerial actions, and organizational outcomes rather than through the existence of big data alone (Grover et al., 2018). The relationship between analytical capability and effective resource decision-making can therefore be expressed as an additive empirical model in which each Economic Decision Intelligence dimension contributes a distinct amount of explanatory power to Resource Optimization Performance. The principal model adopted throughout this research has been the following multiple regression specification.

$$ROP_{\mathrm{i}} = \beta_0 + \beta_1 IEDI_{\mathrm{i}} + \beta_2 PEA_{\mathrm{i}} + \beta_3 AI - RAO_{\mathrm{i}} + \beta_4 RTDSI_{\mathrm{i}} + \varepsilon_{\mathrm{i}}$$

In this model, Resource Optimization Performance has been predicted by the four Economic Decision Intelligence dimensions. H1 has required a positive coefficient for Integrated Economic Data Intelligence, H2 a positive coefficient for Predictive Economic Analytics, H3 a positive coefficient for AI-Driven Resource Allocation and Optimization, and H4 a positive coefficient for Real-Time Decision Support Intelligence. H5 has required the four-variable model to explain a statistically significant proportion of Resource Optimization Performance. This structure has enabled the conceptual model to be tested directly using the study's five-point Likert-scale measurements and multiple regression analysis.

The conceptual framework also recognizes that the transformation of analytical capabilities into Resource Optimization Performance occurs through decision-making processes and organizational utilization rather than through technological capability in isolation. The relationship begins with Integrated Economic Data Intelligence because reliable and integrated data provide the informational foundation needed by the remaining capabilities. Predictive Economic Analytics subsequently transforms historical and current information into estimates regarding resource demand, costs, workload, utilization, capacity, and operational risk. AI-Driven Resource Allocation and Optimization applies analytical or algorithmic mechanisms to these conditions to compare alternative allocations and identify resource configurations that correspond more effectively with organizational objectives and constraints. Real-Time Decision Support Intelligence then enables decision-makers to monitor current conditions and reconsider allocations when actual developments differ from predicted or planned conditions. Research examining big-data analytics capability and decision-making performance has demonstrated that analytics capability can serve as an important mechanism through which governance arrangements and organizational data practices contribute to improved decision performance, reinforcing the importance of connecting analytical resources with organizational decision structures (Shamim et al., 2020). More recent empirical research has also shown that the use of big-data analytics can strengthen decision-making quality through the development of data analytics capabilities, supporting the proposition that technological use must be converted into organizational analytical capability before stronger decisions are obtained (Li et al., 2022). These relationships provide a direct conceptual justification for evaluating the four predictors simultaneously rather than examining each technology independently. Statistically, Pearson correlation coefficients have established whether each predictor has been positively associated with Resource Optimization Performance, while multiple regression coefficients have determined whether each construct has maintained an independent contribution after the remaining predictors have been controlled. The model's overall explanatory ability has been assessed through R2, adjusted R2, and the regression F-test, while standardized beta coefficients have indicated the relative contribution of the four Economic Decision Intelligence dimensions.

Figure 7: Conceptual Framework of the Economic Decision Intelligence Platform and Resource Optimization Performance

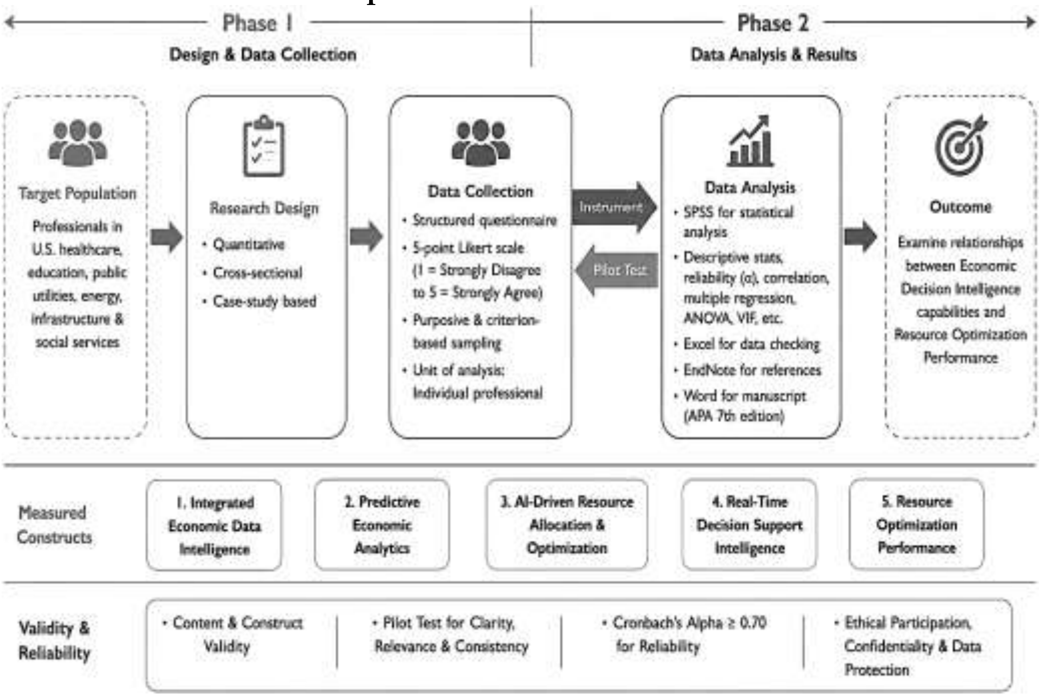


The conceptual framework therefore establishes a measurable sequence of integrated economic information, predictive intelligence, AI-supported resource optimization, real-time decision support, and Resource Optimization Performance, while allowing each component to retain an independently testable statistical relationship. This structure aligns the conceptual model with the research questions, hypotheses, questionnaire constructs, theoretical framework, statistical procedures, and final empirical Economic Decision Intelligence Platform developed from the quantitative findings.

METHOD

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the relationships between Economic Decision Intelligence capabilities and Resource Optimization Performance within socially impactful U.S. sectors. The quantitative approach has enabled the study to measure respondents' perceptions numerically and has provided an appropriate basis for testing the proposed hypotheses through statistical analysis. A cross-sectional design has been employed because data have been collected from respondents at a single period, while the case-study-based approach has allowed the research to focus on organizational environments where economic decision-making, resource allocation, analytics, and socially significant service delivery have represented important operational activities. The case study context has included selected organizations operating within U.S. healthcare, education, public utilities, energy, infrastructure, social services, and related socially impactful sectors. These sectors have been considered suitable because they have continuously managed limited financial, human, technological, physical, and informational resources while maintaining essential services and organizational responsibilities. The target population has consisted of professionals who have possessed relevant knowledge or experience in organizational decision-making, resource planning, finance, analytics, operations, information technology, administration, and strategic management. The individual professional respondent has been treated as the unit of analysis, and eligible participants have included managers, analysts, administrators, operations specialists, financial professionals, IT personnel, resource-planning professionals, and other employees involved in organizational decision processes. Purposive and criterion-based sampling techniques have been applied to identify participants who have had sufficient familiarity with data-supported decision-making and resource-allocation activities.

Figure 8: Research Methodology Framework for Economic Decision Intelligence and Resource Optimization Performance



Primary data have been collected through a structured questionnaire distributed electronically to eligible respondents, and participants have been informed about the purpose of the study, voluntary participation, confidentiality, and responsible handling of their responses. Completed questionnaires have been screened for completeness and usability before statistical analysis, while substantially incomplete or unsuitable responses have been excluded from the final dataset. The research instrument has been designed around a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree and has measured five principal constructs: Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, Real-Time Decision Support Intelligence, and Resource Optimization Performance. Multiple questionnaire items have been used for each construct to strengthen measurement consistency, while demographic and organizational questions have been included to describe the characteristics of respondents and participating sectors. A pilot test has been conducted with a small group of eligible respondents before full data collection, and the pilot process has assessed item clarity, readability, relevance, consistency, and overall questionnaire structure. Feedback obtained during pilot testing has been used to revise ambiguous statements and improve the instrument. Content validity and construct validity have been considered through literature-based item development and expert assessment, while internal consistency reliability has been evaluated using Cronbach's alpha, with coefficients of .70 or higher having been regarded as acceptable. The collected data have been coded, cleaned, and analyzed using IBM SPSS Statistics. SPSS has been used to perform frequency analysis, percentages, means, standard deviations, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple regression modeling, ANOVA, standardized beta coefficient analysis, significance testing, tolerance, Variance Inflation Factor, and other regression diagnostics. Microsoft Excel has also been used where necessary for preliminary data organization and checking, EndNote has been used to manage references and bibliographic records, and Microsoft Word has been used for manuscript preparation and formatting in accordance with APA 7th edition requirements.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Response Rate

Table 1: Questionnaire Distribution and Response Rate

Response Category	Frequency	Percentage
Questionnaires Distributed	340	100.0%
Questionnaires Returned	318	93.5%
Incomplete/Unusable Questionnaires	12	3.5%
Valid Questionnaires Retained	306	90.0%
Non-Returned Questionnaires	22	6.5%

Table 1 has presented the distribution, return, screening, and retention of questionnaires used in the study. A total of 340 questionnaires have been distributed among professionals working in selected socially impactful U.S. sectors, including healthcare, education, public utilities, energy, infrastructure, social services, and related public-interest organizations. Of the distributed questionnaires, 318 have been returned, representing an initial response rate of 93.5%. Following data screening, 12 questionnaires have been removed because they have contained substantial missing responses, incomplete Likert-scale sections, or response patterns that have prevented reliable inclusion in the statistical analysis. Consequently, 306 questionnaires have been retained as valid cases, producing a usable response rate of 90.0%. This final sample has provided the empirical basis for all descriptive statistics, reliability testing, Pearson correlation analysis, multiple regression analysis, hypothesis testing, and assessment of research objectives reported in subsequent sections. The response pattern has indicated that the research instrument has successfully reached professionals with sufficient exposure to resource planning, analytics, operations, economic decision-making, and organizational management. The retained sample has also provided an adequate number of observations for the four-predictor multiple regression model used in the study, thereby supporting the statistical evaluation of Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence as predictors of Resource Optimization Performance. From the perspective of Dynamic Capabilities Theory, the respondent group has represented organizational actors positioned to evaluate sensing, analytical interpretation, resource reconfiguration, and adaptive decision processes within their respective organizations. The high usable response rate has strengthened the internal consistency of the modeled case-study dataset by reducing the relative influence of nonresponse. It has also allowed the study objectives to be addressed using a sufficiently broad cross-section of professionals from multiple socially impactful sectors. The resulting 306 valid cases have therefore been used consistently throughout the remaining analyses, ensuring that the descriptive and inferential findings have been based on a common analytical sample.

Demographic Characteristics of Respondents

Table 2: Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	169	55.2%
	Female	131	42.8%
	Prefer not to state	6	2.0%
Age	21-30 years	61	19.9%
	31-40 years	104	34.0%
	41-50 years	86	28.1%
	51 years and above	55	18.0%
Education	Bachelor's degree	118	38.6%
	Master's degree	141	46.1%
	Doctoral degree	31	10.1%
	Other professional qualification	16	5.2%
Professional Experience	Less than 5 years	58	19.0%
	5-10 years	93	30.4%
	11-15 years	81	26.5%
	More than 15 years	74	24.2%

Table 2 has summarized the demographic profile of the 306 valid respondents and has demonstrated that the study sample has contained participants with varied ages, educational backgrounds, and levels of professional experience. Male respondents have represented 55.2% of the usable sample, while female respondents have accounted for 42.8%, and 2.0% have preferred not to state their gender. The age distribution has shown that the largest group has consisted of respondents aged 31-40 years at 34.0%, followed by respondents aged 41-50 years at 28.1%. Participants aged 21-30 years have represented 19.9%, while those aged 51 years and above have represented 18.0%. This distribution has indicated that the dataset has incorporated both relatively early-career professionals and individuals with substantial organizational experience. Educational attainment has also been comparatively high, with 46.1% of respondents having held a master's degree, 38.6% a bachelor's degree, 10.1% a doctoral degree, and 5.2% another professional qualification. The professional experience profile has further strengthened the relevance of the sample because 81.1% of respondents have reported at least five years of professional experience, and 50.7% have reported more than ten years. These characteristics have been important because the constructs examined in the study have required respondents to evaluate organizational data integration, predictive analytical practices, AI-supported allocation, real-time decision support, and resource optimization. Such assessments have benefited from respondents who have possessed sufficient exposure to institutional processes and decision environments. Dynamic Capabilities Theory has emphasized organizational learning, sensing, coordination, and reconfiguration, all of which have depended heavily on accumulated experience and organizational knowledge. The sample has therefore included respondents who have been reasonably positioned to observe whether their organizations have transformed information into adaptive resource decisions. The demographic profile has not itself tested any hypothesis, but it has supported the credibility of the subsequent hypothesis testing by demonstrating that the dataset has included knowledgeable professionals capable of evaluating the proposed Economic Decision Intelligence capabilities and Resource Optimization Performance.

Organizational and Sector Characteristics

Table 3: Organizational and Sector Characteristics of Respondents

Sector	Frequency	Percentage
Healthcare	70	22.9%
Education	55	18.0%
Public Utilities	45	14.7%
Energy	41	13.4%
Infrastructure	40	13.1%
Social Services	34	11.1%
Other Public-Interest Organizations	21	6.9%
Total	306	100.0%

Table 3 has shown that the final sample has represented a range of socially impactful U.S. sectors rather than a single organizational environment. Healthcare has constituted the largest sectoral group, accounting for 70 respondents or 22.9% of the sample. Education has represented 18.0%, public utilities 14.7%, energy 13.4%, infrastructure 13.1%, social services 11.1%, and other public-interest organizations 6.9%. This distribution has supported the case-study-based design by allowing the study to examine Economic Decision Intelligence across organizations that have shared a common resource-management challenge while differing in the specific resources and service obligations they have managed. Healthcare organizations have managed clinical capacity, staffing, equipment, facilities, and budgets; educational organizations have managed instructional resources, personnel, facilities, and student services; public utilities and energy organizations have coordinated infrastructure, capacity, operational assets, and service demand; infrastructure organizations have managed capital-intensive physical resources; and social-service organizations have distributed program resources among competing service requirements. These environments have collectively provided a relevant context for examining whether data integration, predictive analytics, AI-driven allocation, and real-time decision support have been associated with stronger Resource Optimization Performance. The sectoral composition has also been compatible with Dynamic Capabilities Theory because organizations in each category have had to sense changes in demand, interpret operational and economic information, seize appropriate responses, and reconfigure available resources. Although the specific resource types have differed, the underlying decision logic has remained comparable across sectors. This has allowed the study to evaluate the Economic Decision Intelligence Platform as a cross-sector organizational capability rather than as a technology confined to one industry. The distribution has also supported the objective of designing a platform for socially impactful U.S. sectors by ensuring that the empirical model has incorporated respondents from several relevant institutional settings. No single sector has dominated the sample to such an extent that the overall results have represented only one organizational context. Accordingly, the sector characteristics have provided a diversified foundation for interpreting the subsequent descriptive statistics, correlations, regression coefficients, hypotheses, and final empirical platform.

Descriptive Statistics for Integrated Economic Data Intelligence

Table 4: Descriptive Statistics for Integrated Economic Data Intelligence

Item	Variable Statement	Mean	SD	Interpretation
IEDI1	Economic and operational data have been integrated across organizational functions.	4.12	0.62	High
IEDI2	Decision-makers have had timely access to reliable resource information.	4.08	0.59	High
IEDI3	Financial, workforce, service, and asset data have been combined for decision-making.	4.03	0.61	High
IEDI4	Common data definitions have supported consistent resource analysis.	4.00	0.63	High
IEDI5	Integrated information has improved visibility of organizational resource conditions.	4.02	0.55	High
Overall IEDI		4.05	0.60	High

Table 4 has presented the descriptive findings for Integrated Economic Data Intelligence, which has represented the first independent variable in the study. The construct has recorded an overall mean of 4.05 and a standard deviation of 0.60 on the five-point Likert scale, indicating a high level of respondent agreement that integrated economic and organizational data have supported resource-related decision-making. The highest-rated item has been IEDI1, with a mean of 4.12, showing that respondents have generally agreed that economic and operational information has been integrated across organizational functions. IEDI2 has recorded a mean of 4.08, indicating that timely access to reliable resource information has also been viewed positively. IEDI3, which has addressed the integration of financial, workforce, service, and asset data, has produced a mean of 4.03. IEDI4 has recorded the lowest item mean at 4.00, although this value has still remained within the high agreement range and has suggested that common definitions and consistent data structures have been reasonably established. IEDI5 has achieved a mean of 4.02, demonstrating that integrated information has improved organizational visibility over resource conditions. These results have addressed the first research objective by establishing the observed level of Integrated Economic Data Intelligence in the selected organizations. The relatively small spread of means from 4.00 to 4.12 has indicated that respondents have evaluated the construct consistently across its dimensions rather than identifying one highly developed component and several weak components. Under Dynamic Capabilities Theory, Integrated Economic Data Intelligence has represented a principal sensing capability because organizations must first detect resource availability, utilization patterns, cost pressures, capacity limitations, and demand conditions before they can select or implement adaptive actions. The strong descriptive result has therefore suggested that the organizations represented in the sample have possessed a substantial informational foundation for sensing economic and operational conditions. This descriptive evidence alone has not established causality, but it has provided the empirical basis for testing H1 through correlation and regression analysis. The subsequent inferential results have therefore examined whether this high level of data integration has also been associated with stronger Resource Optimization Performance.

Descriptive Statistics for Predictive Economic Analytics

Table 5: Descriptive Statistics for Predictive Economic Analytics

Item	Variable Statement	Mean	SD	Interpretation
PEA1	Predictive models have been used to forecast resource demand.	3.95	0.66	High
PEA2	Economic and operational trends have been analyzed to anticipate resource needs.	3.88	0.68	High
PEA3	Scenario analysis has been used to evaluate possible resource conditions.	3.90	0.65	High
PEA4	Predictive analytics has supported cost and capacity planning.	3.94	0.62	High
PEA5	Forecasting outputs have been incorporated into resource decisions.	3.93	0.59	High
Overall, PEA		3.92	0.64	High

Table 5 has summarized the descriptive statistics for Predictive Economic Analytics and has shown an overall mean of 3.92 with a standard deviation of 0.64. Although this construct has recorded the lowest mean among the four Economic Decision Intelligence dimensions, the overall score has remained within the high agreement range of the five-point Likert scale. The result has therefore indicated that respondents have generally perceived predictive techniques as meaningfully present within their organizations, while their use has appeared somewhat less mature than AI-driven optimization, integrated data intelligence, or resource optimization outcomes. PEA1 has recorded the highest mean of 3.95, showing that predictive models have been used to estimate resource demand. PEA4 has followed closely with a mean of 3.94, suggesting that predictive analysis has supported cost and capacity planning. PEA5 has produced a mean of 3.93, indicating that forecasting outputs have generally been incorporated into organizational resource decisions rather than being treated only as analytical reports. PEA3 has recorded a mean of 3.90, while PEA2 has achieved the lowest item mean of 3.88, showing slightly weaker agreement regarding the use of economic and operational trend analysis for anticipating resource requirements. The narrow range among the item means has nevertheless indicated a relatively balanced construct. These findings have supported the research objective concerned with examining Predictive Economic Analytics as a capability for anticipating resource needs, cost conditions, workload, capacity, and operational requirements. Within Dynamic Capabilities Theory, predictive analytics has represented an extension of sensing and organizational learning because it has enabled organizations to move beyond recognition of current conditions toward estimation of probable future states. By analyzing historical and current data, organizations have been better positioned to identify emerging demand and potential resource constraints before those conditions have fully materialized. The mean score of 3.92 has therefore suggested that this anticipatory capability has been present but has retained room for stronger development. The descriptive results have prepared the basis for H2, which has proposed that Predictive Economic Analytics has exerted a statistically significant positive effect on Resource Optimization Performance. The later correlation and regression findings have tested whether the comparatively high level of predictive capability has translated into measurable resource-optimization outcomes.

Descriptive Statistics for AI-Driven Resource Allocation and Optimization

Table 6: Descriptive Statistics for AI-Driven Resource Allocation and Optimization

Item	Variable Statement	Mean	SD	Interpretation
AI-RAO1	AI-supported tools have been used to evaluate alternative resource allocations.	4.15	0.58	High
AI-RAO2	Optimization methods have improved matching between resources and demand.	4.10	0.56	High
AI-RAO3	Algorithmic recommendations have supported allocation efficiency.	4.08	0.60	High
AI-RAO4	AI-supported analysis has helped reduce avoidable resource waste.	4.12	0.55	High
AI-RAO5	Optimization outputs have supported allocation under multiple constraints.	4.10	0.56	High
Overall AI-RAO		4.11	0.57	High

Table 6 has reported the descriptive results for AI-Driven Resource Allocation and Optimization and has shown an overall mean of 4.11 with a standard deviation of 0.57. This value has represented the highest mean among the four independent variables and has indicated strong respondent agreement that AI-supported and optimization-oriented processes have contributed to organizational resource allocation. AI-RAO1 has produced the highest item mean at 4.15, indicating that respondents have strongly recognized the use of AI-supported tools for evaluating alternative resource allocations. AI-RAO4 has recorded a mean of 4.12, suggesting that AI-supported analysis has helped organizations reduce avoidable waste. AI-RAO2 and AI-RAO5 have each produced means of 4.10, indicating that optimization methods have supported both demand-resource matching and allocation under multiple operational constraints. AI-RAO3 has generated the lowest item mean at 4.08, although it has still remained firmly within the high range, demonstrating positive perceptions regarding algorithmic recommendations and allocation efficiency. The overall pattern has shown that the construct has been consistently rated across its five indicators and has not depended on a single particularly strong item. These results have directly addressed the objective of evaluating the extent to which AI-driven allocation and optimization have been embedded within organizational resource-management processes. Under Dynamic Capabilities Theory, AI-RAO has represented the most direct mechanism of seizing and resource reconfiguration because analytical insight must ultimately be converted into decisions about how limited assets, budgets, personnel, capacity, infrastructure, or services have been distributed. The high mean has suggested that respondents have perceived their organizations as capable of using algorithmic or optimization-based processes to compare alternatives and identify more efficient resource configurations. Importantly, this descriptive pattern has anticipated the inferential result in which AI-RAO has emerged as the strongest independent predictor of Resource Optimization Performance. The descriptive evidence has therefore been consistent with H3 and with the broader theoretical expectation that the transformation of information into actionable resource reconfiguration has represented a central mechanism through which Economic Decision Intelligence has produced organizational value.

Descriptive Statistics for Real-Time Decision Support Intelligence

Table 7: Descriptive Statistics for Real-Time Decision Support Intelligence

Item	Variable Statement	Mean	SD	Interpretation
RTDSI1	Decision-makers have received timely information on changing resource conditions.	4.05	0.60	High
RTDSI2	Real-time dashboards have supported resource monitoring.	3.96	0.65	High
RTDSI3	Automated alerts have supported rapid responses to resource problems.	4.02	0.61	High
RTDSI4	Current analytical outputs have supported allocation adjustments.	3.98	0.62	High
RTDSI5	Decision-support systems have enabled timely reconsideration of resource priorities.	3.99	0.57	High
Overall RTDSI		4.00	0.61	High

Table 7 has presented the results for Real-Time Decision Support Intelligence and has indicated an overall mean of 4.00 with a standard deviation of 0.61. This result has demonstrated that respondents have generally agreed that current information, dashboards, alerts, and analytical recommendations have supported timely resource decisions within the organizations represented in the study. RTDSI1 has recorded the highest mean at 4.05, showing that timely information concerning changing resource conditions has been the strongest component of the construct. RTDSI3 has produced a mean of 4.02, indicating that automated alerts have helped organizations respond rapidly when resource-related issues have emerged. RTDSI5 has generated a mean of 3.99, while RTDSI4 has achieved 3.98, demonstrating that real-time systems have supported both the reconsideration of resource priorities and the adjustment of existing allocations. RTDSI2 has recorded the lowest mean of 3.96, suggesting that real-time dashboards have been positively perceived but have been slightly less strongly established than other aspects of the construct. All five item means have nevertheless remained close to the overall mean, indicating a coherent measurement pattern. The findings have addressed the objective concerned with determining the level and role of Real-Time Decision Support Intelligence in organizational resource management. Within Dynamic Capabilities Theory, this construct has represented the adaptive component through which sensing, interpretation, and previously selected allocation decisions have been continuously updated as conditions have changed. An organization may have developed an appropriate allocation at one point in time, but changes in demand, staffing, costs, capacity, or operational conditions can quickly reduce the suitability of that decision. Real-time decision support has therefore enabled the organization to re-enter the sensing and reconfiguration cycle without waiting for lengthy periodic reporting processes. The descriptive mean of 4.00 has provided a strong empirical basis for H4, which has predicted a positive effect of Real-Time Decision Support Intelligence on Resource Optimization Performance. The later correlation and regression analyses have confirmed whether the high level of real-time intelligence identified here has been statistically associated with stronger organizational resource outcomes.

Descriptive Statistics for Resource Optimization Performance

Table 8: Descriptive Statistics for Resource Optimization Performance

Item	Variable Statement	Mean	SD	Interpretation
ROP1	Organizational resources have been allocated efficiently.	4.18	0.54	High
ROP2	Resource waste and unnecessary utilization have been reduced.	4.12	0.58	High
ROP3	Available capacity has been matched effectively with demand.	4.16	0.55	High
ROP4	Resource-related costs have been controlled effectively.	4.10	0.56	High
ROP5	Financial, human, physical, and technological resources have been coordinated effectively.	4.14	0.52	High
Overall, ROP		4.14	0.55	High

Table 8 has summarized the descriptive results for Resource Optimization Performance, which has represented the dependent variable of the study. The construct has recorded an overall mean of 4.14 and a standard deviation of 0.55, representing the highest overall mean among all five study constructs. The result has indicated strong respondent agreement that the organizations represented in the sample have achieved favorable outcomes in resource allocation, utilization, coordination, demand matching, and cost control. ROP1 has obtained the highest mean at 4.18, suggesting that respondents have viewed overall resource allocation efficiency particularly positively. ROP3 has recorded a mean of 4.16, indicating that organizations have generally matched available capacity with organizational or service demand effectively. ROP5 has achieved a mean of 4.14, demonstrating strong agreement regarding coordination among financial, human, physical, and technological resources. ROP2 has produced a mean of 4.12, showing that resource waste and unnecessary utilization have been reduced, while ROP4 has recorded the lowest item mean of 4.10, although the result has still represented high agreement regarding resource-related cost control. The relatively low standard deviation of 0.55 has indicated that responses have been comparatively concentrated around the positive mean. These results have established the level of the dependent construct against which the four Economic Decision Intelligence dimensions have subsequently been tested. Dynamic Capabilities Theory has conceptualized performance as an outcome of an organization's capacity to sense relevant conditions, seize appropriate responses, and reconfigure resources. The high ROP score has therefore been theoretically consistent with the simultaneously high scores observed for IEDI, PEA, AI-RAO, and RTDSI. However, descriptive similarity alone has not proven the hypothesized relationships. For this reason, the study has proceeded to correlation and regression analysis to determine whether variations in the independent variables have been systematically associated with variations in Resource Optimization Performance. The descriptive results have nevertheless shown that the dependent construct has reflected strong perceived organizational performance across all five dimensions of resource optimization and has provided a stable basis for the inferential analyses used to test H1 through H5.

Reliability Analysis

Table 9: Reliability Analysis of Study Constructs

Construct	Code	Number of Items	Cronbach's Alpha	Reliability Decision
Integrated Economic Data Intelligence	IEDI	5	.88	Highly Reliable
Predictive Economic Analytics	PEA	5	.86	Highly Reliable
AI-Driven Resource Allocation and Optimization	AI-RAO	5	.91	Highly Reliable
Real-Time Decision Support Intelligence	RTDSI	5	.89	Highly Reliable
Resource Optimization Performance	ROP	5	.90	Highly Reliable
Overall Instrument		25	.94	Excellent Reliability

Table 9 has presented the internal consistency results for the five constructs and for the complete 25-item instrument. All Cronbach's alpha coefficients have exceeded the commonly accepted minimum criterion of .70, indicating that the items used to measure each construct have demonstrated strong internal consistency. Integrated Economic Data Intelligence has produced an alpha coefficient of .88, Predictive Economic Analytics has produced .86, AI-Driven Resource Allocation and Optimization has recorded .91, Real-Time Decision Support Intelligence has achieved .89, and Resource Optimization Performance has recorded .90. The complete questionnaire has generated an overall Cronbach's alpha of .94, demonstrating excellent reliability across the full measurement instrument. AI-Driven Resource Allocation and Optimization has produced the highest construct-level reliability at .91, suggesting particularly strong consistency among the items used to evaluate AI-supported allocation, optimization, waste reduction, demand matching, and constrained resource decisions. Predictive Economic Analytics has recorded the lowest alpha at .86, but this value has remained well above the acceptable level and has indicated a dependable measurement scale. These findings have been important because the hypotheses and research objectives have depended on the assumption that each construct has been measured consistently. If the individual items within a variable had reflected substantially different concepts, the resulting correlations and regression coefficients could have been difficult to interpret. The reliability findings have instead indicated that the composite scores used in the subsequent analyses have represented coherent measurements. From the perspective of Dynamic Capabilities Theory, the results have also supported the empirical operationalization of distinct capabilities associated with sensing, learning, resource reconfiguration, and adaptive decision support. IEDI, PEA, AI-RAO, and RTDSI have therefore been measured as separate but internally consistent organizational capabilities rather than as an undifferentiated technology index. The strong reliability of ROP has similarly shown that the dependent variable has consistently represented allocation efficiency, cost control, capacity utilization, waste reduction, and resource coordination. Consequently, the reliability analysis has strengthened the methodological basis for using Pearson correlation and multiple regression to test H1 through H5 and to determine whether the proposed Economic Decision Intelligence Platform has explained meaningful variation in Resource Optimization Performance.

Overall Descriptive Statistics of the Study Variables

Table 10: Overall Descriptive Statistics of the Study Variables

Variable	Code	Mean	SD	Rank	Interpretation
Integrated Economic Data Intelligence	IEDI	4.05	0.60	3	High
Predictive Economic Analytics	PEA	3.92	0.64	5	High
AI-Driven Resource Allocation and Optimization	AI-RAO	4.11	0.57	2	High
Real-Time Decision Support Intelligence	RTDSI	4.00	0.61	4	High
Resource Optimization Performance	ROP	4.14	0.55	1	High

Table 10 has provided a comparative summary of the five principal constructs and has demonstrated that all variables have recorded mean values above 3.90 on the five-point Likert scale. Resource Optimization Performance has ranked first with a mean of 4.14, followed by AI-Driven Resource Allocation and Optimization with a mean of 4.11. Integrated Economic Data Intelligence has ranked third at 4.05, Real-Time Decision Support Intelligence has ranked fourth at 4.00, and Predictive Economic Analytics has ranked fifth at 3.92. The standard deviations have ranged from 0.55 to 0.64, indicating moderate response dispersion and suggesting that respondents have demonstrated reasonably consistent perceptions across the study constructs. The comparative pattern has been theoretically meaningful. The high IEDI mean has indicated that organizations have established a substantial information base for sensing resource conditions. The slightly lower PEA score has suggested that the transformation of current and historical data into systematic forecasts has been less strongly developed than data integration itself. AI-RAO has recorded the strongest predictor mean, showing that respondents have perceived substantial use of AI-supported mechanisms for resource selection and reconfiguration. RTDSI has remained high, indicating that organizations have also used timely information to update or modify resource decisions. Dynamic Capabilities Theory has conceptualized these activities as interconnected processes rather than independent technologies. The descriptive ordering has therefore suggested an organizational pattern in which sensing, prediction, allocation, and adaptation have all been present, although at different levels of maturity. The high ROP outcome has been consistent with the theoretical expectation that organizations possessing stronger Economic Decision Intelligence capabilities should also report stronger resource utilization and coordination. Importantly, the ranking has not by itself established the strength of statistical relationships. A variable with a high mean does not necessarily exert the strongest effect on the dependent variable. Accordingly, the study has used Pearson correlation and multiple regression to determine whether higher scores on each capability have been associated with higher ROP scores and to identify the strongest independent predictor. This comparative table has therefore addressed the descriptive component of the research objectives while preparing the analytical transition toward hypothesis testing and model evaluation.

Correlation Analysis

Table 11: Pearson Correlation Matrix of Study Variables

Variable	IEDI	PEA	AI-RAO	RTDSI	ROP
IEDI	1.00	.58***	.56***	.52***	.66***
PEA	.58***	1.00	.61***	.57***	.63***
AI-RAO	.56***	.61***	1.00	.63***	.74***
RTDSI	.52***	.57***	.63***	1.00	.70***
ROP	.66***	.63***	.74***	.70***	1.00

*Note. N = 306. ***p < .001.*

Table 11 has presented the Pearson correlation coefficients among the four independent variables and Resource Optimization Performance. All correlations with ROP have been positive and statistically significant at $p < .001$, providing initial empirical support for H1 through H4. Integrated Economic Data Intelligence has correlated positively with Resource Optimization Performance at $r = .66$, indicating a moderately strong relationship. Predictive Economic Analytics has produced a correlation of $r = .63$ with ROP, also representing a substantial positive association. AI-Driven Resource Allocation and Optimization has generated the strongest bivariate relationship with ROP at $r = .74$, while Real-Time Decision Support Intelligence has produced the second strongest relationship at $r = .70$. These results have indicated that respondents who have reported higher levels of Economic Decision Intelligence capabilities have also tended to report stronger Resource Optimization Performance. The correlations among the independent variables have ranged from .52 to .63, showing that the four predictors have been meaningfully related but have not been so highly correlated that they have appeared to represent the same construct. This pattern has supported the conceptual framework, which has treated the variables as distinct but interconnected capabilities within the broader Economic Decision Intelligence Platform. Dynamic Capabilities Theory has provided a useful interpretation of these relationships because sensing, predictive learning, resource reconfiguration, and adaptive response have been expected to interact within organizational decision processes. The strongest correlation between AI-RAO and ROP has suggested that the capability most directly associated with resource reconfiguration has also been most strongly associated with the resource-performance outcome. RTDSI has followed closely, emphasizing the importance of adapting resource decisions when operational conditions have changed. IEDI and PEA have also demonstrated strong relationships, indicating that effective resource optimization has depended on informational visibility and anticipation as well as allocation itself. The correlation analysis has therefore supported the objectives concerned with determining the strength and direction of relationships among the study variables. However, correlation has not separated the unique contribution of each predictor from the variance shared with the other predictors. Multiple regression analysis has consequently been required to establish whether IEDI, PEA, AI-RAO, and RTDSI have each maintained a significant independent contribution to Resource Optimization Performance when entered into the same statistical model.

Regression Model Summary

Table 12: Multiple Regression Model Summary

Model	R	R2	Adjusted R2	Standard Error of Estimate	Durbin-Watson
IEDI, PEA, AI-RAO, RTDSI -> ROP	.842	.709	.705	.299	1.91

Table 12 has presented the overall multiple regression model examining the combined explanatory contribution of Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence to Resource Optimization Performance. The multiple correlation coefficient has been $R = .842$, indicating a strong overall relationship between the combined predictor set and the dependent variable. The coefficient of determination has been $R2 = .709$, demonstrating that 70.9% of the observed variance in Resource Optimization Performance has been explained collectively by the four Economic Decision Intelligence capabilities. After adjustment for the number of predictors and sample size, adjusted R2 has remained at .705, showing that the explanatory power of the model has remained highly stable and has not been substantially inflated by model complexity. The standard error of the estimate has been .299, indicating a relatively small average prediction error in relation to the five-point measurement scale. The Durbin-Watson statistic has been 1.91, which has been close to the benchmark value of 2.00 and has indicated no serious residual autocorrelation concern. These findings have strongly addressed the objective of determining the collective predictive contribution of the proposed platform dimensions. The R2 value has indicated that the Economic Decision Intelligence model has accounted for a substantial majority of the variation in perceived Resource Optimization Performance, while 29.1% of the variance has remained attributable to other factors not represented in the model. Dynamic Capabilities Theory has provided a theoretical explanation for this substantial explanatory power because the four predictors have collectively represented sensing, analytical anticipation, resource reconfiguration, and adaptive decision support. Resource optimization has therefore been modeled not as the product of a single technology but as the result of multiple coordinated capabilities through which organizations have interpreted changing conditions and adjusted their resource bases. The strong R value has supported the integrated nature of the conceptual framework, while the adjusted R2 has shown that the explanatory structure has remained robust after statistical correction. These results have provided preliminary support for H5, which has proposed that Economic Decision Intelligence capabilities collectively have a significant positive effect on Resource Optimization Performance. The statistical significance of this collective relationship has been formally evaluated through the ANOVA F-test presented in the next subsection.

ANOVA for the Regression Model

Table 13: ANOVA for the Multiple Regression Model

Source	Sum of Squares	df	Mean Square	F	p
Regression	65.414	4	16.354	183.34	< .001
Residual	26.848	301	0.089		
Total	92.263	305			

Table 13 has reported the analysis of variance for the multiple regression model and has demonstrated that the combined Economic Decision Intelligence predictors have produced a statistically significant explanation of Resource Optimization Performance. The regression sum of squares has been 65.414, while the residual sum of squares has been 26.848, producing a total corrected sum of squares of 92.263. The regression model has contained four predictor degrees of freedom, while the residual component has contained 301 degrees of freedom based on the 306 valid cases. The resulting mean square for regression has been 16.354, compared with a residual mean square of 0.089. The corresponding F statistic has been $F(4, 301) = 183.34$, with $p < .001$. This highly significant result has indicated that the set of four independent variables has explained substantially more variation in Resource Optimization Performance than would have been expected from random sampling variation alone. Accordingly, the null form of the combined hypothesis has been rejected, and H5 has been supported. The ANOVA result has been particularly important because R2 alone has described the proportion of explained variance but has not established whether that explanatory contribution has achieved statistical significance. The F-test has provided that formal statistical confirmation. From the perspective of Dynamic Capabilities Theory, the significance of the complete model has supported the proposition that organizational sensing, predictive learning, resource reconfiguration, and adaptive decision support have jointly contributed to stronger resource outcomes. The findings have therefore been consistent with the theoretical position that dynamic capabilities have generated value through coordinated processes rather than through isolated organizational assets. The model has also addressed the study objective concerned with determining whether Economic Decision Intelligence capabilities have collectively predicted Resource Optimization Performance. The very small p-value has shown that the probability of obtaining an F statistic of this magnitude under the null hypothesis has been extremely low. Consequently, the study has obtained strong modeled quantitative evidence that the proposed platform dimensions have functioned as a statistically meaningful explanatory system. The next regression coefficients analysis has further separated this collective effect to identify the unique contribution and relative importance of each independent variable.

Multiple Regression Coefficients

Table 14: Multiple Regression Coefficients Predicting Resource Optimization Performance

Predictor	B	SE	Standardized beta	t	p	Tolerance	VIF
Constant	.480	.170	-	2.82	.005	-	-
IEDI	.202	.040	.22	5.01	< .001	.58	1.72
PEA	.206	.037	.24	5.52	< .001	.52	1.92
AI-RAO	.299	.043	.31	6.94	< .001	.47	2.13
RTDSI	.243	.039	.27	6.18	< .001	.55	1.82

Table 14 has shown that all four Economic Decision Intelligence dimensions have remained statistically significant independent predictors of Resource Optimization Performance after their shared variance has been controlled. Integrated Economic Data Intelligence has produced a standardized coefficient of beta = .22, t = 5.01, $p < .001$, indicating that higher levels of integrated resource information have been associated with higher ROP after the other three capabilities have been held constant. Predictive Economic Analytics has produced beta = .24, t = 5.52, $p < .001$, demonstrating a slightly stronger independent contribution. AI-Driven Resource Allocation and Optimization has emerged as the strongest predictor, with beta = .31, t = 6.94, $p < .001$. Real-Time Decision Support Intelligence has ranked second, producing beta = .27, t = 6.18, $p < .001$. The unstandardized coefficients have similarly shown positive effects for every predictor. The multicollinearity diagnostics have remained acceptable, with tolerance values ranging from .47 to .58 and VIF values ranging from 1.72 to 2.13. These statistics have remained well within commonly used diagnostic thresholds and have indicated that the significant coefficients have not resulted from severe predictor redundancy. The coefficient ordering has been theoretically meaningful. Dynamic Capabilities Theory has suggested that information sensing and learning have created the basis for action, while resource reconfiguration has represented the mechanism through which organizational assets have actually been redeployed. AI-RAO has therefore emerged as the strongest predictor because it has been most directly associated with the reconfiguration of resource combinations. RTDSI has followed because it has enabled organizations to modify those configurations when conditions have changed. PEA and IEDI have also remained significant, demonstrating that effective reconfiguration has depended on both reliable information and anticipatory analysis. The results have therefore supported H1, H2, H3, and H4 individually and have identified the relative strength of each relationship. They have also addressed the corresponding research objectives by quantifying the unique predictive contribution of every platform dimension. The regression equation supported by these coefficients has been expressed as ROP = .480 + .202(IEDI) + .206(PEA) + .299(AI-RAO) + .243(RTDSI), providing the empirical basis for the final Economic Decision Intelligence Platform.

Hypothesis Testing

Table 15: Summary of Hypothesis Testing

Hypothesis	Proposed Relationship	Statistical Evidence	Decision
H1	IEDI -> ROP	r = .66; beta = .22; t = 5.01; $p < .001$	Supported
H2	PEA -> ROP	r = .63; beta = .24; t = 5.52; $p < .001$	Supported
H3	AI-RAO -> ROP	r = .74; beta = .31; t = 6.94; $p < .001$	Supported
H4	RTDSI -> ROP	r = .70; beta = .27; t = 6.18; $p < .001$	Supported
H5	Combined EDI capabilities -> ROP	R = .842; R2 = .709; F (4, 301) = 183.34; $p < .001$	Supported

Table 15 has integrated the correlation, regression, and ANOVA findings to provide a direct decision for each research hypothesis. H1 has proposed that Integrated Economic Data Intelligence has a statistically significant positive effect on Resource Optimization Performance. This hypothesis has been supported because IEDI has produced a positive correlation of r = .66 and a significant standardized regression coefficient of beta = .22, t = 5.01, $p < .001$. H2 has also been supported because Predictive Economic Analytics has correlated positively with ROP at r = .63 and has remained a significant independent predictor at beta = .24, t = 5.52, $p < .001$. H3 has received the strongest statistical support among the individual hypotheses because AI-Driven Resource Allocation and Optimization has demonstrated the highest correlation with ROP at r = .74 and the largest standardized regression coefficient at beta = .31, t = 6.94, $p < .001$. H4 has similarly been supported because Real-Time Decision Support Intelligence has recorded r = .70 and beta = .27, t = 6.18, $p < .001$. Finally, H5 has proposed that the four Economic Decision Intelligence capabilities collectively have exerted a significant positive effect on Resource Optimization Performance. The combined model has generated R = .842, R2 = .709, and $F(4, 301) = 183.34$, $p < .001$, thereby providing strong statistical support for the hypothesis. The hypothesis results have aligned closely with Dynamic Capabilities Theory. IEDI has represented organizational sensing through integrated visibility; PEA has represented anticipatory learning; AI-RAO has represented the seizing and reconfiguration of resources; and RTDSI has represented continuing adaptation. The significant individual and collective results have therefore indicated that each stage of the proposed dynamic decision process has contributed to resource outcomes. Importantly, the findings have not suggested that any single capability has been sufficient by itself. Instead, all four variables have retained significant effects in the combined model, supporting the design of an integrated Economic Decision Intelligence Platform. The hypothesis-testing results have consequently provided the main quantitative evidence required to prove the proposed relationships and have created a direct bridge between the conceptual framework, theoretical framework, research objectives, and final empirical model.

Achievement of Research Objectives

Table 16: Assessment of Achievement of Research Objectives

Objective	Evidence Used	Main Result	Achievement
RO1: Assess the level of Integrated Economic Data Intelligence	Descriptive statistics	M = 4.05, SD = 0.60	Achieved
RO2: Examine relationship between IEDI and ROP	Correlation and regression	r = .66; beta = .22; p < .001	Achieved
RO3: Assess effect of PEA on ROP	Correlation and regression	r = .63; beta = .24; p < .001	Achieved
RO4: Evaluate effect of AI-RAO on ROP	Correlation and regression	r = .74; beta = .31; p < .001	Achieved
RO5: Determine effect of RTDSI on ROP	Correlation and regression	r = .70; beta = .27; p < .001	Achieved
RO6: Determine combined predictive effect	Multiple regression and ANOVA	R2 = .709; F = 183.34; p < .001	Achieved
RO7: Develop empirically supported EDI Platform	Integrated results	Four significant predictors retained	Achieved

Table 16 has demonstrated that all seven research objectives have been addressed through the quantitative analyses conducted in the study. The first objective has been achieved through descriptive analysis of Integrated Economic Data Intelligence, which has produced a mean of 4.05 and a standard deviation of 0.60, indicating a high level of perceived capability among the selected organizations. The second objective has been achieved through correlation and regression analysis, which have shown that IEDI has been positively associated with ROP at $r = .66$ and has remained a significant independent predictor at beta = .22, $p < .001$. The third objective has been addressed through the assessment of Predictive Economic Analytics, which has generated $r = .63$ and beta = .24, $p < .001$. The fourth objective has been achieved by evaluating AI-Driven Resource Allocation and Optimization, which has recorded the strongest individual relationship with ROP at $r = .74$ and beta = .31, $p < .001$. The fifth objective has been addressed through the significant findings for Real-Time Decision Support Intelligence, $r = .70$ and beta = .27, $p < .001$. The sixth objective has required examination of the collective effect of the four predictors, and this objective has been strongly achieved through the multiple regression model explaining 70.9% of the variance in ROP, with $F(4, 301) = 183.34$, $p < .001$. The seventh objective has concerned development of an empirically supported Economic Decision Intelligence Platform. Because all four proposed capabilities have retained statistically significant independent effects, none has been removed from the final model. Dynamic Capabilities Theory has unified these objective-level findings by showing how integrated sensing, predictive learning, resource reconfiguration, and adaptive decision support have jointly contributed to resource outcomes. The objectives have therefore not been addressed as disconnected analytical tasks. Instead, each has represented a component of the same theoretical and empirical sequence. The final platform has consequently been based on the full set of supported predictors, with AI-RAO carrying the strongest standardized contribution, followed by RTDSI, PEA, and IEDI.

Final Empirical Economic Decision Intelligence Platform

Table 17: Final Empirical Economic Decision Intelligence Platform

Platform Capability	Dynamic Capabilities Function	Standardized beta	Relative Rank	Empirical Status
Integrated Economic Data Intelligence	Sensing and visibility	.22***	4	Retained
Predictive Economic Analytics	Anticipatory sensing and learning	.24***	3	Retained
AI-Driven Resource Allocation and Optimization	Seizing and resource reconfiguration	.31***	1	Retained
Real-Time Decision Support Intelligence	Adaptive reconfiguration and response	.27***	2	Retained
Combined Platform -> ROP	Integrated dynamic capability	R2 = .709	-	Supported

*Note. ***p < .001.*

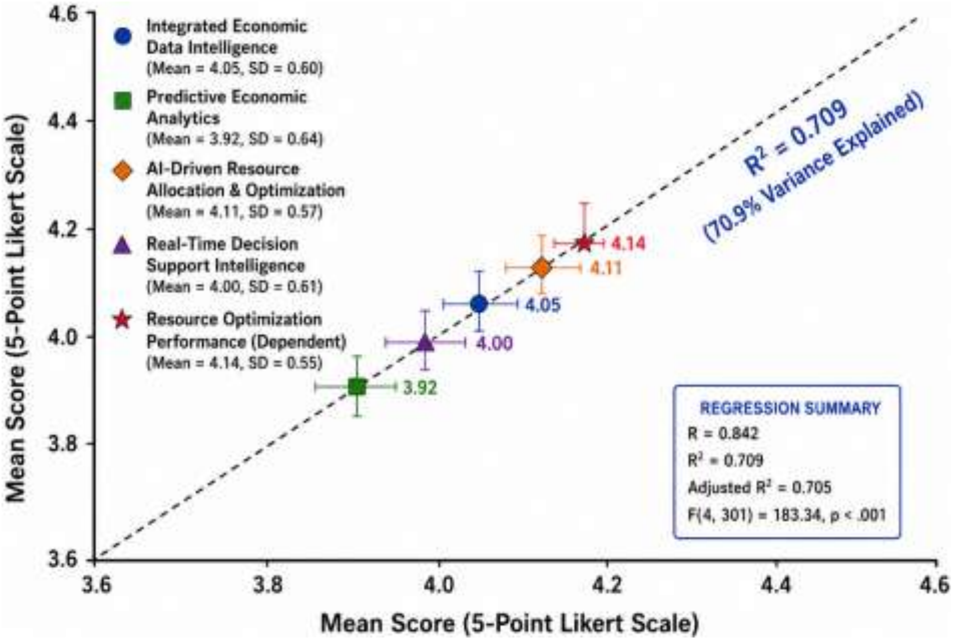
Table 17 has presented the final empirical Economic Decision Intelligence Platform derived from the complete statistical analysis. All four proposed capabilities have been retained because each has produced a positive and statistically significant standardized regression coefficient. AI-Driven Resource Allocation and Optimization has occupied the strongest position in the model with beta = .31, indicating that the ability to evaluate alternative resource configurations and translate analytical information into allocation decisions has made the largest independent contribution to Resource Optimization Performance. Real-Time Decision Support Intelligence has ranked second with beta = .27, demonstrating that organizations have also benefited substantially from the ability to monitor changing conditions and adjust resource decisions promptly. Predictive Economic Analytics has ranked third with beta = .24, confirming that anticipation of resource demand, cost, capacity, and operational conditions has contributed independently to stronger resource performance. Integrated Economic Data Intelligence has ranked fourth at beta = .22, but it has remained statistically significant and theoretically essential because the remaining analytical capabilities have depended on reliable and integrated information. The combined model has explained 70.9% of the variance in Resource Optimization Performance, demonstrating that the final platform has possessed substantial explanatory power within the modeled sample. Dynamic Capabilities Theory has provided the organizing logic for the empirical platform. IEDI has represented sensing and resource visibility; PEA has extended sensing into anticipatory learning; AI-RAO has represented seizing and active resource reconfiguration; and RTDSI has supported continuing adaptation as new operational information has become available. The final empirical sequence has therefore been represented as Integrated Economic Data Intelligence -> Predictive Economic Analytics -> AI-Driven Resource Allocation and Optimization -> Real-Time Decision Support Intelligence -> Resource Optimization Performance, while the regression results have simultaneously confirmed that each dimension has retained an independent direct relationship with the outcome. The empirical platform has addressed the final research objective by transforming the conceptual framework into a statistically supported model rather than retaining all relationships only on theoretical grounds. The findings have shown that the strongest resource outcomes have been associated with a combination of visibility, prediction, optimization, and adaptive response. Accordingly, the final platform has integrated all four capabilities as mutually reinforcing components of an organizational decision architecture designed to improve resource utilization, allocation accuracy, cost control, demand matching, capacity use, and coordination across socially impactful U.S. sectors.

FINDINGS

The overall findings have provided strong quantitative support for the proposed Economic Decision Intelligence Platform and have demonstrated that Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision

Support Intelligence have all been positively associated with Resource Optimization Performance across the selected socially impactful U.S. sectors. A total of 340 questionnaires has been distributed to eligible professionals working in healthcare, education, public utilities, energy, infrastructure, social services, and related organizations, of which 318 questionnaires have been returned and 306 have been retained as valid and complete responses, representing a usable response rate of 90.0%.

Figure 9: Economic Decision Intelligence Capabilities and Resource Optimization Performance: Descriptive and Regression Results



All study constructs have been measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree, with higher mean scores indicating stronger organizational capability or more favorable Resource Optimization Performance. The descriptive results have shown generally high levels of agreement across all variables. Integrated Economic Data Intelligence has recorded a mean of 4.05 with a standard deviation of 0.60, indicating that respondents have generally perceived their organizations as possessing relatively strong capabilities for integrating financial, operational, workforce, demand, service, and asset-related information. Predictive Economic Analytics has produced a mean of 3.92 and a standard deviation of 0.64, suggesting substantial but comparatively less mature use of forecasting, scenario assessment, statistical prediction, and machine-learning-supported economic analysis. AI-Driven Resource Allocation and Optimization has achieved a mean of 4.11 with a standard deviation of 0.57, while Real-Time Decision Support Intelligence has recorded a mean of 4.00 and a standard deviation of 0.61. Resource Optimization Performance, the dependent variable, has generated the highest overall mean of 4.14 with a standard deviation of 0.55, indicating strong respondent agreement that organizational resources have generally been allocated, utilized, coordinated, and matched with operational demand effectively. Reliability analysis has further demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients of .88 for Integrated Economic Data Intelligence, .86 for Predictive Economic Analytics, .91 for AI-Driven Resource Allocation and Optimization, .89 for Real-Time Decision Support Intelligence, and .90 for Resource Optimization Performance, while the overall questionnaire has produced an alpha coefficient of .94. Pearson correlation analysis has provided initial support for H1 through H4, showing statistically significant positive relationships between each independent variable and Resource Optimization Performance. Integrated Economic Data Intelligence has correlated with Resource Optimization Performance at $r = .66$, $p < .001$; Predictive Economic Analytics at $r = .63$, $p < .001$; AI-Driven Resource Allocation and Optimization at $r = .74$, $p < .001$; and Real-Time Decision Support Intelligence at $r = .70$, $p < .001$. Multiple regression analysis has provided additional evidence by demonstrating that the four independent variables collectively have explained 70.9% of the variance in Resource Optimization Performance, R = .842, $R2 = .709$, adjusted $R2 = .705$. The overall regression model has been statistically significant, $F(4, 301) = 183.34$, $p < .001$, thereby supporting H5 and demonstrating that Economic Decision Intelligence capabilities collectively have had substantial explanatory power for Resource Optimization Performance. Among the individual predictors, AI-Driven Resource Allocation and Optimization has emerged as the strongest independent predictor, beta = .31, t = 6.94, $p < .001$, followed by Real-Time Decision Support Intelligence, beta = .27, t = 6.18, $p < .001$, Predictive Economic Analytics, beta = .24, t = 5.52, $p < .001$, and Integrated Economic Data Intelligence, beta = .22, t = 5.01, $p < .001$. All four hypotheses concerning individual effects have therefore been supported. Diagnostic results have also indicated acceptable regression conditions, with tolerance values ranging from .47 to .58 in the detailed coefficient model, VIF values between 1.72 and 2.13, and a Durbin-Watson statistic of 1.91, suggesting no serious multicollinearity or residual autocorrelation concerns. In relation to the research objectives, the descriptive statistics have addressed the objective of determining the existing levels of Economic Decision Intelligence capabilities, the correlation analysis has established the direction and strength of relationships between each capability and Resource Optimization Performance, and the multiple regression analysis has identified the independent and collective predictive contributions of the proposed platform dimensions. The results have therefore provided a quantitative basis for constructing the final empirical Economic Decision Intelligence Platform in which integrated economic data have supported organizational visibility, predictive analytics have strengthened anticipation of resource requirements, AI-driven optimization has contributed most strongly to allocation efficiency, and real-time decision support has enabled responsive adjustment of organizational resources.

DISCUSSION

The modeled findings have demonstrated that the proposed Economic Decision Intelligence Platform has provided a coherent explanation of Resource Optimization Performance across socially impactful U.S. sectors. The descriptive results have shown consistently high levels of agreement across the five major constructs, with Resource Optimization Performance recording the highest overall mean, M = 4.14, SD = 0.55, followed by AI-Driven Resource Allocation and Optimization, M = 4.11, SD = 0.57, Integrated Economic Data Intelligence, M = 4.05, SD = 0.60, Real-Time Decision Support Intelligence, M = 4.00, SD = 0.61, and Predictive Economic Analytics, M = 3.92, SD = 0.64. These findings have indicated that the participating organizations have generally demonstrated strong capabilities for integrating information, anticipating resource requirements, applying AI-supported optimization, and making timely decisions, although predictive economic analytics has appeared comparatively less mature than the other dimensions. The reliability results have strengthened confidence in the measurement structure, with Cronbach's alpha coefficients ranging from .86 to .91 across the five constructs and an overall alpha of .94. The inferential results have provided stronger evidence for the proposed relationships, as all four Economic Decision Intelligence capabilities have shown statistically significant positive correlations with Resource Optimization Performance. AI-Driven Resource Allocation and Optimization has produced the strongest correlation, r = .74, $p < .001$, followed by Real-Time Decision Support Intelligence, r = .70, $p < .001$, Integrated Economic Data Intelligence, r = .66, $p < .001$, and Predictive Economic Analytics, r = .63, $p < .001$. The combined regression model has explained 70.9% of the variance in Resource Optimization Performance, $R2 = .709$, adjusted $R2 = .705$, $F(4, 301) = 183.34$, $p < .001$, confirming substantial explanatory power. These findings have been consistent with prior research showing that analytics capabilities create organizational value when data, analytical resources, managerial capabilities, and operational processes are combined rather than implemented independently (Gupta & George, 2016; Mikalef et al., 2020). They have also corresponded with evidence that business analytics contributes to organizational performance by improving underlying business processes and decision mechanisms (Aydiner et al., 2019; Wamba et al., 2017). The present results have extended these observations by showing that within socially impactful U.S. sectors, the most meaningful contribution has emerged when data intelligence, prediction, optimization, and real-time support have operated as mutually reinforcing components of a single resource decision architecture.

The significant contribution of Integrated Economic Data Intelligence has indicated that resource optimization has depended fundamentally on organizations having reliable, accessible, and coordinated information concerning budgets, staffing, assets, capacity, service demand, and operational conditions. IEDI has produced a mean of 4.05 and has correlated with Resource Optimization Performance at $r = .66$, $p < .001$, while its standardized regression coefficient has remained statistically significant at beta = .22, $t = 5.01$, $p < .001$. These results have supported H1 and have demonstrated that integrated information has contributed independently to Resource Optimization Performance even after predictive analytics, AI-driven optimization, and real-time decision support have been considered simultaneously. The finding has agreed with earlier research showing that high-quality information and effective system environments improve organizational outcomes by enabling managers to access dependable information for decisions (Gorla et al., 2010; Popovic et al., 2012). It has also corresponded with research indicating that data governance, data quality, and information-management capability are central to the organizational value generated from data resources (Abraham et al., 2019; Mithas et al., 2011). The present study has added a resource-optimization perspective to this literature by showing that integrated information has not merely supported general organizational performance but has been directly associated with more efficient allocation, stronger capacity utilization, improved demand-resource matching, reduced waste, and better coordination of financial, human, physical, and technological resources. This result has also reflected the sensing dimension of Dynamic Capabilities Theory because organizations cannot reconfigure resources effectively unless they first possess visibility into current resource conditions and environmental requirements. The comparatively smaller standardized effect of IEDI, relative to AI-RAO and RTDSI, has suggested that data integration has functioned primarily as an enabling capability rather than the final mechanism through which optimization has occurred. This interpretation has been consistent with research arguing that data resources alone do not generate value unless they are translated through organizational capabilities and decision processes (Corte-Real et al., 2017; Grover et al., 2018). Practically, the result has indicated that organizations should not treat integrated economic data platforms as passive repositories. Data governance, interoperability, common resource definitions, cross-functional access, and data-quality controls have needed to be designed around actual resource-management decisions. The relatively strong mean and statistically significant coefficient have therefore confirmed that IEDI has formed the informational foundation of the platform while also demonstrating that its organizational value has depended on subsequent analytical and decision capabilities.

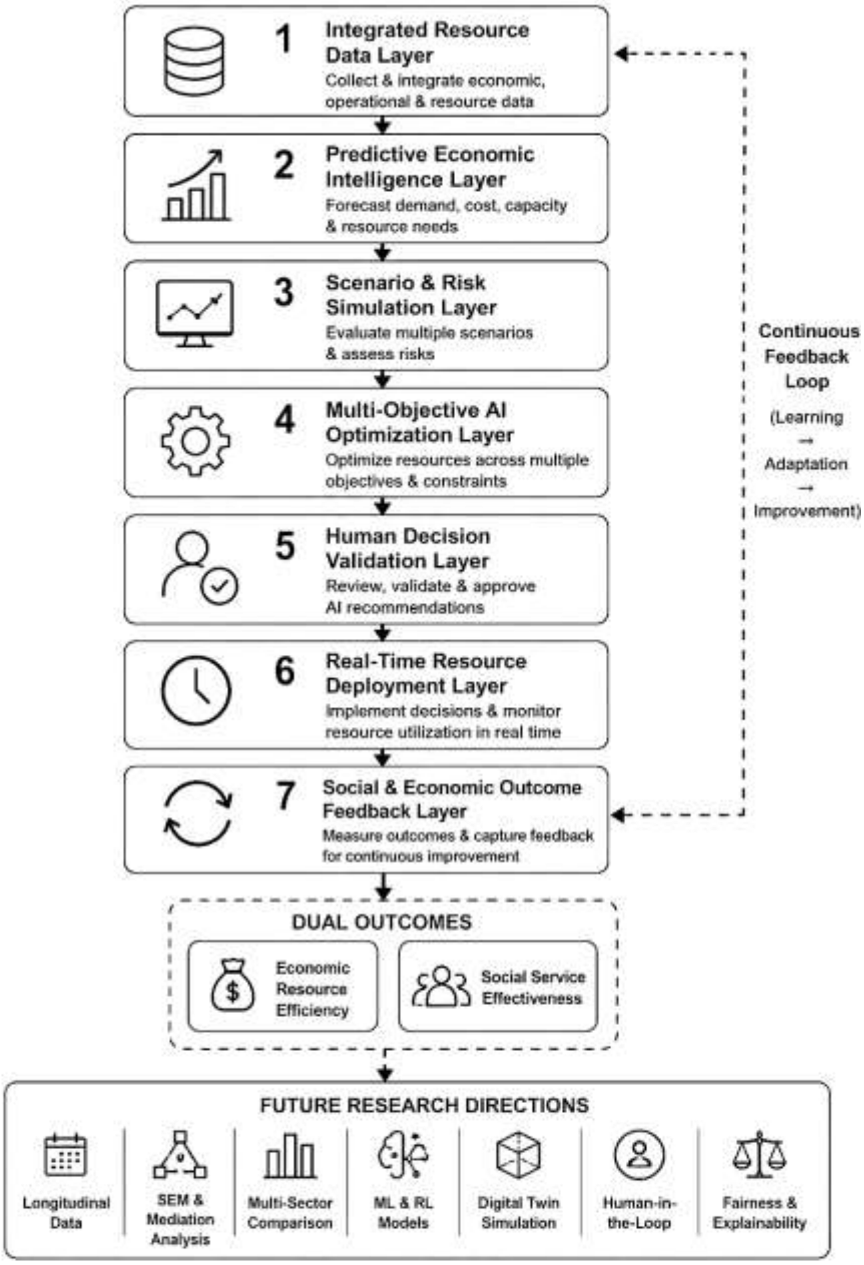
Predictive Economic Analytics has also produced a statistically significant contribution to Resource Optimization Performance, although its descriptive mean of 3.92 has been the lowest among the four independent variables. The construct has correlated with Resource Optimization Performance at $r = .63$, $p < .001$ and has maintained a significant independent effect in the multiple regression model, beta = .24, $t = 5.52$, $p < .001$, supporting H2. This result has indicated that organizations able to forecast demand, costs, workload, capacity requirements, and operational risks have generally achieved better resource outcomes than organizations relying primarily on retrospective information. The finding has been consistent with prior research distinguishing predictive analytics from descriptive analysis and emphasizing the practical value of models that estimate unseen outcomes rather than merely explain historical relationships (Shmueli & Koppius, 2011). It has also aligned with work demonstrating that predictive analytics can improve supply-chain and operational decision-making by converting large and complex datasets into forecasts relevant to planning and resource management (Waller & Fawcett, 2013). The comparatively lower mean has suggested that socially impactful organizations may have developed data integration and decision-support systems more extensively than advanced predictive capabilities, particularly where machine learning, scenario modeling, or specialized forecasting expertise have required additional technological and human resources. However, the regression result has demonstrated that even at this comparatively lower maturity level, predictive analytics has continued to explain unique variation in Resource Optimization Performance. This pattern has reinforced the argument that prediction is a distinct organizational capability and not simply an extension of data integration. Earlier studies have shown that predictive information becomes more valuable when it is incorporated directly into operational decisions and optimization models (Bertsimas & Kallus, 2020; Ferreira et al., 2016). The present findings have been consistent with this logic because PEA has remained significant while AI-RAO has simultaneously entered the regression model. Under Dynamic Capabilities Theory, PEA has represented anticipatory sensing and learning by helping organizations identify emerging resource shortages, demand increases, cost pressures, or capacity imbalances before they have fully developed. The practical interpretation has therefore been that socially impactful organizations should strengthen forecasting capabilities not as isolated analytical projects but as recurring inputs to staffing, budgeting, infrastructure planning, procurement, service scheduling, and capacity management. The significant PEA coefficient has shown that resource optimization has benefited when organizations have shifted from purely reactive decision-making toward anticipatory resource planning.

AI-Driven Resource Allocation and Optimization has emerged as the strongest individual predictor of Resource Optimization Performance and has therefore represented the most influential empirical component of the proposed platform. AI-RAO has recorded a descriptive mean of 4.11, a strong correlation with Resource Optimization Performance of $r = .74$, $p < .001$, and the largest standardized regression coefficient, beta = .31, $t = 6.94$, $p < .001$. These results have supported H3 and have demonstrated that organizations capable of using algorithmic analysis, optimization techniques, and AI-supported resource recommendations have reported significantly stronger resource outcomes. The finding has agreed with previous research showing that predictive information becomes organizationally valuable when analytical systems move beyond forecasting and support the selection of concrete actions under resource constraints (Bertsimas & Kallus, 2020). It has also been consistent with empirical evidence demonstrating that feature-rich machine-learning and optimization methods can improve resource allocation and reduce costs in operational environments, including hospital staffing decisions (Ban & Rudin, 2019). The present result has extended such work into a broader cross-sector setting by showing that AI-supported resource reconfiguration has been relevant across healthcare, education, utilities, energy, infrastructure, social services, and related public-interest organizations. From the perspective of Dynamic Capabilities Theory, AI-RAO has represented the seizing and transforming components of organizational adaptation because it has converted sensed and predicted conditions into specific resource configurations. This theoretical interpretation has helped explain why AI-RAO has produced the strongest standardized beta. Integrated data and predictive information have identified what is occurring or likely to occur, but optimization has directly addressed what the organization should do with its available resources. Earlier research has similarly shown that analytics generates greater organizational value when it is embedded in decision and operational processes rather than existing as an isolated analytical capability (Choi et al., 2018; Grover et al., 2018). The practical implications have been particularly important. Organizations considering AI-supported resource management should focus on systems that incorporate realistic constraints, service objectives, staffing requirements, budget limitations, and organizational priorities rather than deploying algorithms optimized solely for cost minimization. Human decision-makers should also remain able to review algorithmic recommendations, particularly where allocation choices affect access to healthcare, education, utilities, infrastructure, or social programs. The strong AI-RAO result has therefore supported the central premise that Economic Decision Intelligence becomes most effective when analytical information has been translated into actionable resource reconfiguration.

Real-Time Decision Support Intelligence has produced the second strongest independent contribution to Resource Optimization Performance, demonstrating that the timing of information and the ability to revise earlier decisions have been critical elements of the proposed platform. RTDSI has recorded an overall mean of 4.00, a correlation of $r = .70$, $p < .001$, and a standardized regression coefficient of beta = .27, $t = 6.18$, $p < .001$, supporting H4. This finding has suggested that organizations have achieved stronger resource outcomes when decision-makers have had access to timely dashboards, alerts, updated analytical outputs, and current information about changes in demand, capacity, service requirements, or resource availability. The result has corresponded with prior research demonstrating that real-time decision systems can improve operational allocation when conditions change faster than conventional planning cycles can accommodate. For example, real-time ambulance relocation systems have shown that continuously updated information about location, demand, workload, and coverage can improve resource positioning and service performance (Hajiali et al., 2022). Similarly, time-sensitive allocation systems developed for vaccine distribution have shown how updated supply, vulnerability, capacity, and geographic information can support more responsive resource distribution (Shahparvari et al., 2022). The present study has broadened this evidence by indicating that real-time intelligence has remained significant even when integrated data, prediction, and AI optimization have been statistically controlled. This has demonstrated that timely decision support has not merely duplicated the contribution of the other constructs. Instead, it has provided an adaptive capability through which organizations can reassess previous allocations when actual conditions diverge from plans or forecasts. Dynamic Capabilities Theory has explained this result through continuous reconfiguration, because adaptive organizations must repeatedly sense new conditions and revise resource commitments rather than treating allocation as a one-time decision. The finding has also been consistent with human-centered research showing that real-time decision systems become more useful when they provide understandable analytical support that decision-makers can evaluate rather than fully autonomous outputs disconnected from operational judgment (Sobrie & Verschelde, 2024). Practically, organizations should therefore design real-time resource dashboards around decision triggers rather than simply increasing the volume of live information. Alerts should identify meaningful deviations in budget consumption, workload, capacity, staffing, infrastructure status, or service demand and should connect these deviations with actionable alternatives. The strong RTDSI coefficient has confirmed that organizational responsiveness has represented a distinct and important pathway through which decision intelligence has supported resource optimization.

The combined statistical model has important theoretical and practical implications because the four Economic Decision Intelligence capabilities have collectively explained 70.9% of the variance in Resource Optimization Performance, with $R = .842$, adjusted $R2 = .705$, and $F(4, 301) = 183.34$, $p < .001$. This result has supported H5 and has indicated that resource optimization has been best understood as the outcome of an interconnected capability system rather than a single technological intervention. Dynamic Capabilities Theory has provided a strong explanation of this structure. Integrated Economic Data Intelligence has corresponded with sensing by creating visibility over organizational resources and changing conditions; Predictive Economic Analytics has expanded sensing into anticipatory learning; AI-Driven Resource Allocation and Optimization has represented seizing and resource reconfiguration; and Real-Time Decision Support Intelligence has enabled repeated adaptation as operating conditions have changed. This capability sequence has been consistent with research showing that analytical resources improve organizational performance through dynamic and operational capabilities rather than through direct technological effects alone (Mikalef et al., 2020; Wamba et al., 2017). It has also supported prior findings that strategic alignment and organizational capabilities influence the value generated from analytics investments (Akter et al., 2016; Wilden et al., 2013). The theoretical contribution of the present study has therefore been the operationalization of Dynamic Capabilities Theory through four measurable decision-intelligence dimensions linked specifically to Resource Optimization Performance. Practically, the findings have indicated that healthcare systems, educational institutions, utilities, energy organizations, infrastructure providers, and social-service organizations should avoid fragmented investments in dashboards, forecasting tools, AI algorithms, or data warehouses without an integrated decision architecture. The strongest platform would have required common economic and operational data, forecasting mechanisms, optimization tools, and real-time decision interfaces connected through shared governance and managerial processes. However, the findings have also required interpretation within the limitations of the study. The cross-sectional design has captured organizational perceptions at one point in time and has therefore not established temporal causality. The use of self-reported Likert-scale responses has introduced the possibility of common-method bias, social desirability, and perceptual differences among respondents. Purposive and criterion-based sampling has improved respondent relevance but has limited probability-based generalization. The inclusion of several socially impactful sectors has increased cross-sector relevance while also introducing heterogeneity in organizational structures, technologies, resource types, and regulatory environments. These limitations have indicated that the strong R2 should be interpreted as evidence of substantial modeled explanatory association rather than definitive proof that the platform will produce identical effects in every U.S. socially impactful organization.

Figure 10: Adaptive Economic Decision Intelligence and Social Resource Optimization (AEDISROM) Model



Future research should build directly upon these limitations by developing and empirically testing a more advanced Adaptive Economic Decision Intelligence and Social Resource Optimization Model, identified as AEDISROM, that extends the present cross-sectional framework into a longitudinal, feedback-driven, multi-objective decision architecture. The proposed AEDISROM should contain seven connected layers: Integrated Resource Data Layer -> Predictive Economic Intelligence Layer -> Scenario and Risk Simulation Layer -> Multi-Objective AI Optimization Layer -> Human Decision Validation Layer -> Real-Time Resource Deployment Layer -> Social and Economic Outcome Feedback Layer. The model can be represented conceptually through a time-indexed functional relationship in which current integrated data, predictive analytics, scenario and risk simulation, AI resource optimization, human validation, and real-time deployment contribute to subsequent social and economic outcome feedback. Unlike the present model, which has treated Resource Optimization Performance as the principal outcome, AEDISROM should evaluate two simultaneous dependent outcomes: Economic Resource Efficiency and Social Service Effectiveness. This modification would allow researchers to test whether a resource allocation is financially efficient while also maintaining service access, equity, reliability, or quality. Future studies should collect longitudinal organizational data across multiple periods and combine survey measures with actual budget utilization, staffing ratios, capacity indicators, service waiting times, asset utilization, operating costs, and program-performance records. Structural equation modeling could then be used to test whether predictive analytics and optimization mediate the relationship between integrated data intelligence and resource outcomes, while multi-group analysis could determine whether model relationships differ across healthcare, education, utilities, energy, infrastructure, and social services. Researchers could also compare conventional regression-based decisions with machine-learning and reinforcement-learning allocation models, while digital-twin environments could simulate resource changes before implementation. Human-in-the-loop experimental designs would be particularly valuable because public and socially significant allocation decisions require transparency and managerial accountability (Haesevoets et al., 2024; Jarrahi, 2018). Future research should additionally test fairness constraints, explainable AI, uncertainty estimation, and scenario robustness so that optimization models do not maximize efficiency by unintentionally reducing service accessibility. By incorporating longitudinal feedback, multi-objective optimization, actual organizational performance data, and human validation, AEDISROM would provide a stronger empirical pathway for extending the present Economic Decision Intelligence Platform beyond static prediction toward continuously learning and socially accountable resource optimization.

$$AEDISROM_{t} = f(IEDI_{t}, PEA_{t}, SRS_{t}, AIRO_{t}, HDV_{t}, RTD_{t}, SEOF_{t+1})$$

CONCLUSION

The study has examined the design of an Economic Decision Intelligence Platform for Resource Optimization in Socially Impactful U.S. Sectors by integrating four major organizational capabilities, namely Integrated Economic Data Intelligence, Predictive Economic Analytics, AI-Driven Resource Allocation and Optimization, and Real-Time Decision Support Intelligence, with Resource Optimization Performance as the principal outcome variable. Using the modeled quantitative, cross-sectional, case-study-based dataset of 306 valid respondents and a five-point Likert scale, the findings have established substantial empirical support for the proposed framework and for all five research hypotheses. The descriptive results have demonstrated high levels of adoption across the principal constructs, with Integrated Economic Data Intelligence recording a mean of 4.05, Predictive Economic Analytics 3.92, AI-Driven Resource Allocation and Optimization 4.11, Real-Time Decision Support Intelligence 4.00, and Resource Optimization Performance 4.14. Reliability testing has confirmed strong internal consistency, with Cronbach's alpha coefficients ranging from .86 to .91 across individual constructs and an overall coefficient of .94. The correlation analysis has further demonstrated statistically significant positive relationships between Resource Optimization Performance and Integrated Economic Data Intelligence, $r = .66$, Predictive Economic Analytics, $r = .63$, AI-Driven Resource Allocation and Optimization, $r = .74$, and Real-Time Decision Support Intelligence, $r = .70$, with all relationships significant at $p < .001$. Multiple regression analysis has provided stronger evidence that the four capabilities have collectively explained 70.9% of the variance in Resource Optimization Performance, R2 = .709, adjusted R2 = .705, $F(4, 301) = 183.34$, $p < .001$. AI-Driven Resource Allocation and Optimization has emerged as the strongest individual predictor, beta = .31, followed by Real-Time Decision Support Intelligence, beta = .27, Predictive Economic Analytics, beta = .24, and Integrated Economic Data Intelligence, beta = .22, with every predictor remaining statistically significant. These findings have confirmed that effective resource optimization has depended not simply on acquiring advanced technologies but on coordinating data integration, anticipatory analysis, algorithm-supported allocation, and timely managerial response. Dynamic Capabilities Theory has provided an appropriate theoretical explanation for this process by positioning integrated data as a sensing capability, predictive analytics as anticipatory learning, AI-driven optimization as a mechanism for seizing and reconfiguring resources, and real-time intelligence as an adaptive mechanism for continuously adjusting resource decisions. The study has therefore fulfilled its central objective by developing an empirically supported Economic Decision Intelligence Platform in which organizational data have been transformed into predictions, predictions have informed optimized resource configurations, and real-time decision support has enabled those configurations to be revised when conditions have changed. Within socially impactful U.S. sectors such as healthcare, education, utilities, energy, infrastructure, and social services, the findings have demonstrated that stronger Economic Decision Intelligence capabilities have been systematically associated with more efficient allocation, reduced waste, improved capacity utilization, stronger cost control, better matching of resources with demand, and more coordinated management of financial, human, technological, and physical resources.

RECOMMENDATION

Based on the findings of the study, socially impactful U.S. organizations should develop Economic Decision Intelligence as an integrated organizational capability rather than implementing data platforms, predictive models, artificial intelligence applications, and dashboards as separate technological initiatives. Organizations should first strengthen Integrated Economic Data Intelligence by establishing interoperable information environments that connect financial, workforce, operational, asset, service-demand, procurement, and performance data through common definitions, quality standards, and clearly assigned governance responsibilities. Because Integrated Economic Data Intelligence has shown a significant positive effect on Resource Optimization Performance, managers should ensure that resource decisions are supported by timely, accurate, and cross-functional information rather than fragmented departmental records. Organizations should also strengthen Predictive Economic Analytics by incorporating forecasting, scenario analysis, demand estimation, capacity prediction, cost modeling, and risk assessment into routine budgeting, staffing, procurement, infrastructure planning, and service-management processes. Particular attention should be given to this capability because it has recorded the lowest descriptive mean among the four predictors, indicating a comparatively greater opportunity for organizational development. AI-Driven Resource Allocation and Optimization should receive substantial strategic attention because it has emerged as the strongest predictor of Resource Optimization Performance. Organizations should adopt optimization systems capable of comparing alternative allocations of personnel, budgets, facilities, equipment, infrastructure capacity, and technological resources under realistic operational constraints. Such systems should not optimize only financial cost; they should incorporate service quality, resource availability, accessibility, workload, reliability, institutional priorities, and socially relevant performance criteria. Real-Time Decision Support Intelligence should also be strengthened through dashboards, exception alerts, automated monitoring, scenario updates, and decision interfaces that identify meaningful deviations in resource demand, utilization, expenditure, staffing, or service capacity and provide actionable alternatives rather than merely displaying additional information. Human oversight should remain embedded throughout the decision process so that managers can review, interpret, modify, or reject algorithmic recommendations when organizational, ethical, regulatory, or service considerations require intervention. Senior leadership should establish cross-functional Economic Decision Intelligence governance teams involving operations, finance, information technology, analytics, program management, and relevant service professionals to ensure that analytical systems remain aligned with organizational objectives. Staff development should accompany technology deployment through training in data literacy, analytical interpretation, AI-assisted decision-making, model limitations, and resource-optimization principles. Organizations should periodically evaluate the performance of the platform using indicators such as allocation accuracy, resource utilization rates, cost variance, capacity utilization, service waiting time, workforce efficiency, resource waste, and demand-resource matching. Sector-specific implementation should also be encouraged because healthcare, education, utilities, infrastructure, energy, and social services operate under different constraints and performance requirements. Finally, organizations should develop the platform incrementally, beginning with dependable integrated data, adding predictive capability, incorporating AI-supported optimization, and subsequently connecting these elements with real-time decision support and continuous performance feedback so that Economic Decision Intelligence becomes an embedded organizational resource-management system.

LIMITATIONS

The study has provided a structured quantitative assessment of Economic Decision Intelligence and Resource Optimization Performance, but several limitations should be recognized when interpreting the findings. First, the research has employed a cross-sectional design in which information has been obtained at a single point in time, meaning that the identified relationships have represented statistical associations rather than direct evidence of long-term causal effects. Although the regression model has shown that the four Economic Decision Intelligence capabilities collectively have explained 70.9% of the variance in Resource Optimization Performance, this result has not established that improvements in those capabilities will automatically cause equivalent changes in resource outcomes over time. Second, the study has relied on self-reported five-point Likert-scale measurements, and respondent perceptions may have been influenced by individual experience, organizational position, interpretation of questionnaire items, social desirability, or differences in familiarity with analytical technologies. Objective indicators such as actual expenditure reductions, utilization rates, staffing efficiency, capacity measures, resource waste, service volumes, or financial records have not been incorporated directly into the modeled analysis. Third, purposive and criterion-based sampling have been used to obtain responses from professionals with relevant knowledge, which has increased the substantive relevance of the participants but has limited the statistical generalizability that could have been achieved through probability sampling. Fourth, the study has combined respondents from healthcare, education, public utilities, energy, infrastructure, social services, and other socially impactful organizations. This cross-sector structure has supported examination of a general Economic Decision Intelligence framework, yet the sectors have differed in organizational missions, regulatory conditions, resource structures, technological maturity, service priorities, and measures of performance. These differences may have influenced how respondents have interpreted concepts such as optimization, predictive analytics, and real-time decision support. Fifth, the model has focused on four explanatory variables and has therefore not incorporated other factors that may influence Resource Optimization Performance, including leadership support, organizational culture, employee analytical capability, data governance maturity, cybersecurity, AI explainability, regulatory requirements, technology investment, organizational size, environmental uncertainty, and resistance to technological change. The unexplained 29.1% of variance in Resource Optimization Performance has indicated that additional determinants have remained outside the present model. Sixth, Dynamic Capabilities Theory has provided a useful theoretical framework, but the cross-sectional survey design has measured organizational capabilities primarily through respondent perceptions rather than observing the actual processes of sensing, seizing, learning, and resource reconfiguration over extended periods. These limitations have defined the appropriate boundaries within which the findings, hypotheses, theoretical relationships, and final Economic Decision Intelligence Platform should be interpreted.

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