ASRC Procedia
Global Perspectives in Science and Scholarship
Florida, USA

Volume: 1; **Issue:** 1
Pages: 1700– 1739
Published: 29 April 2025

open access

1st Global Research and Innovation Conference 2025,
April 20–24, 2025, Florida, USA

AI-Driven Distribution Planning for Essential Goods in Underserved Communities: A Mixed Methods Framework for Access Optimization

Md Shahab Uddin[1]:

[1]. *Director, Consumer Products Distribution Business, Bangladesh;*
Email: shopno23@gmail.com

Doi: 10.63125/chv6qf37
Peer-review under responsibility of the organizing committee of GRIC, 2025

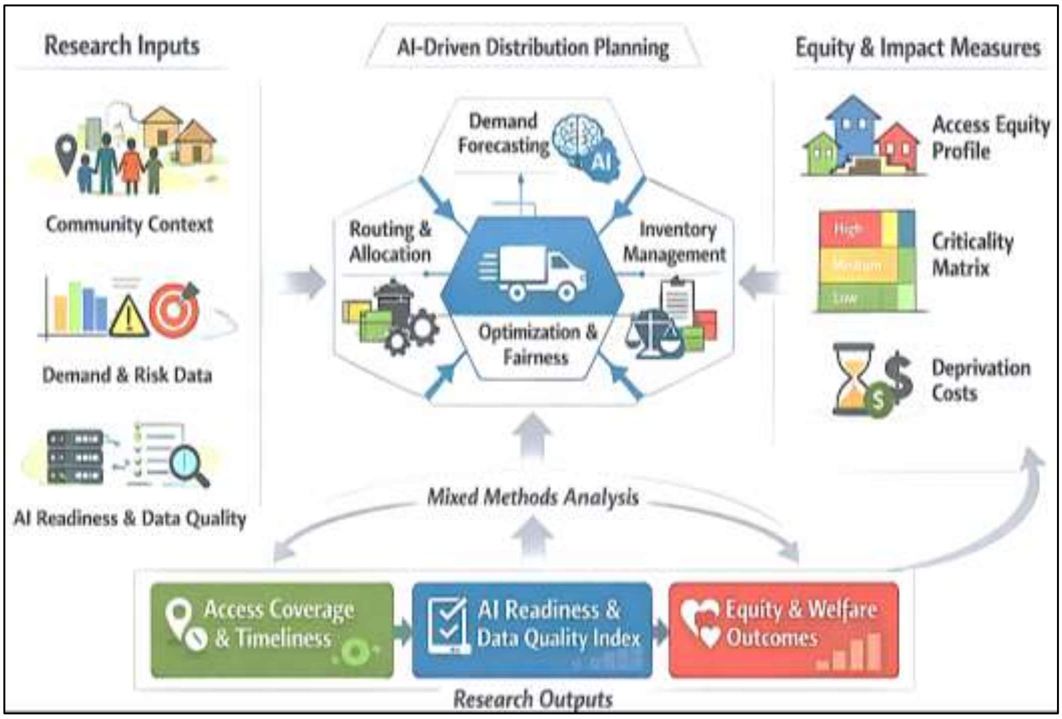
Abstract
This study examined how underserved communities experience moderate to low and uneven access to essential goods due to last-mile distribution planning that is constrained by unreliable data, partial workflow embedding, and volatile operating conditions. The purpose was to quantify how AI-driven distribution planning capability improves access optimization within cloud and enterprise distribution contexts, while accounting for technology, organizational, and environmental conditions. Using a quantitative, cross-sectional, case-based design, a structured five-point Likert survey captured system-level perceptions from 312 valid respondents (78.0% usable) out of 400 invited and 320 completed, spanning planners/coordinators (22.4%), field and delivery staff (27.6%), retail or community distribution points (18.9%), NGO or partner actors (11.5%), and beneficiaries (19.6%). Access Optimization (AO) was modeled as the outcome, with AI Planning Capability (AIPC), Data Quality and Integration (DQI), Organizational Readiness and Embeddedness (ORG_READY), Environmental Support (ENV_SUPPORT), and Constraint Severity (CONSTRAINTS) as predictors. The analysis included reliability testing, descriptive statistics, Pearson correlations, and multiple regression with collinearity diagnostics. Measurement reliability was strong across constructs (AO α = .91; AIPC α = .88; DQI α = .86; ORG_READY α = .89; ENV_SUPPORT α = .82; CONSTRAINTS α = .79). Baseline access was constrained (AO M = 2.84, SD = 0.76) alongside high operational constraints (M = 3.74, SD = 0.62), moderate AI capability (AIPC M = 3.27, SD = 0.71), and moderate organizational readiness (M = 3.12, SD = 0.69). Equity profiling revealed meaningful disparity, with the lowest access cluster reporting AO M = 2.41 versus 3.18 in the highest access cluster (gap = 0.77; inequity index = 0.21). Bivariate results aligned with the conceptual model, showing positive associations between AO and AIPC (r = .52), DQI (r = .47), ORG_READY (r = .55), and ENV_SUPPORT (r = .32), and a negative association with CONSTRAINTS (r = −.41). The regression model was significant and explanatory (R^2 = .45; Adj. R^2 = .44; F (5,306) = 49.8, p < .001; VIF 1.22–2.05), with ORG_READY as the strongest predictor (β = .29), followed by AIPC (β = .24) and DQI (β = .18). Results indicate that AI-enabled planning can improve access, but realized gains depend on data integration, organizational embedding, and targeted interventions to narrow subarea gaps under persistent constraints.

Keywords
AI-Driven Distribution Planning; Access Optimization; Underserved Communities; TOE Framework; Data Quality and Organizational Readiness;

INTRODUCTION

Access optimization in distribution planning refers to the systematic design of how essential goods move from supply points to end users so that the right items arrive at the right locations within acceptable time, cost, and service constraints, while accounting for demand uncertainty, infrastructure limits, and operational risk (Akbari & Do, 2021). In humanitarian logistics and essential-goods contexts, "last-mile distribution" is commonly defined as the final stage that delivers commodities from local distribution nodes to beneficiaries, where operational decisions such as routing, allocation, and scheduling directly shape the lived experience of access (Baharmand et al., 2022). "Underserved communities" can be operationalized as populations experiencing persistent barriers to acquiring essential goods—such as food, medicine, hygiene items, and emergency supplies—because of structural constraints (distance, affordability, service gaps, mobility), supply volatility, and unequal allocation patterns. Internationally, these access constraints appear in disaster relief operations, chronic food insecurity, and public health supply systems, where distribution networks must balance efficiency with fairness and continuity of service at scale (Bambra et al., 2021).

Figure 1: AI-Driven Distribution Planning Framework for Access Optimization in Underserved Communities



The global significance of this problem is anchored in the reality that essential-goods supply chains operate across borders and institutions, frequently under disruption and with incomplete information, and that distribution failures create measurable losses in welfare through delayed delivery, unmet demand, and inequitable coverage (Beamon & Balcik, 2008). In supply chain research, distribution planning is treated as a decision domain that spans strategic design (facility location, network structure), tactical planning (allocation policies, replenishment), and operational execution (vehicle routing, delivery frequency). Across these layers, the quality of access is shaped by how decision-makers translate population need into service targets, then translate targets into routes, quantities, and time windows (Carbonneau et al., 2008). Humanitarian logistics scholarship emphasized that these operations often involve many actors with fragmented data and urgency-driven constraints that require structured decision support, not ad hoc dispatching (Feizabadi, 2020). In parallel, the analytics literature formalized how data-driven planning leverages descriptive, predictive, and prescriptive methods to improve decisions when systems are complex and information is imperfect. Within this framing, AI-driven distribution planning refers to the use of machine learning for forecasting and classification, and optimization/heuristics for route-and-allocation decisions, supported by data pipelines that ensure reliability, timeliness, and relevance of input signals. Because essential-goods access is both a service-performance outcome and an equity outcome, definitions in this research area extend beyond cost and distance to include timeliness, continuity, and fairness in who receives what and when (Gutjahr & Fischer, 2018).

Distribution planning for essential goods becomes analytically distinct when the objective is not only to maximize delivered volume, but also to reduce human deprivation associated with delayed or absent access. Humanitarian logistics research elevated this perspective by proposing objective functions that incorporate "social costs," combining logistics costs with deprivation costs representing the welfare loss from not having access to required goods over time (Haque & Arifur, 2020; Hazen et al., 2016; Rauf, 2018). This concept is important for underserved communities because access is rarely binary; it accumulates across time as shortages repeat, deliveries arrive late, and households adopt coping strategies that impose additional burdens. The deprivation-cost framing gives a structured way to represent the time-sensitive nature of essential goods, where the urgency of food, water, medicine, and hygiene supplies may differ, and where the marginal harm of delay can increase as time passes without replenishment (Haque & Md. Arifur, 2021; Holguín-Veras et al., 2016; Ashraful et al., 2020). Equity is central in this same literature because distribution plans that minimize totals can still produce extreme disparities across locations, and disparities often map onto vulnerability and infrastructure disadvantage. A key operational reality is that last-mile distribution happens under scarce resources—limited vehicles, limited inventory, uncertain resupply, and disrupted road networks—so trade-offs emerge between serving more people quickly and serving all communities fairly (Jinnat & Kamrul, 2021; Fokhrul et al., 2021; Orgut et al., 2018). Research on equity and deprivation argued that fairness is not automatically achieved by minimizing deprivation costs alone under budget constraints and recommended explicit inequity measures such as Gini-based terms alongside deprivation-based objectives (Fahimul, 2022; Nguyen et al., 2018; Zaman et al., 2021). Related studies model equity as constraints or additional objectives and show that delivery-time equity, quantity equity, and deprivation-time equity can behave differently depending on network structure and delivery policies. In practice-oriented contexts, food-bank distribution research similarly treats equity as a measurable performance dimension, recognizing that limited supply and heterogeneous local capacity can generate systematic over-service in some zones and under-service in others (Ransikarbum et al., 2020). These strands collectively establish that essential-goods distribution is not only a routing problem but also a welfare allocation problem with ethical and operational stakes (Hammad, 2022; Hasan & Waladur, 2022; Parappathodi & Archetti, 2022). This study's title foregrounds "access optimization" because access can be defined through multiple measurable constructs—coverage, frequency, timeliness, and perceived availability—and each construct can be tied to planning variables such as delivery frequency, route structure, inventory release policies, and allocation rules (Rashid & Sai Praveen, 2022; Arifur & Haque, 2022; Reihaneh & Ghoniem, 2017). In underserved communities, access optimization also requires sensitivity to infrastructure variability, data gaps, and localized demand patterns, which motivates a research design that can quantify relationships between AI-enabled planning practices and access outcomes in a real case setting.

AI-driven distribution planning has two tightly connected roles: (a) improving informational accuracy about demand, constraints, and risk, and (b) improving decision quality in routing and allocation under those informational inputs (Towhidul et al., 2022; Rifat & Jinnat, 2022; Steenbergen et al., 2023). Predictive analytics research in supply chains documented that demand signals can be distorted and incomplete, and that machine learning methods can be applied to forecast demand in settings affected by information asymmetry and bullwhip effects, with performance comparable to or better than traditional baselines depending on context. In essential-goods distribution, predictive performance matters because demand estimation errors propagate into inventory positioning, route plans, and service-frequency decisions, with direct consequences for stockouts and delayed deliveries (Wassenhove, 2006). The supply chain analytics literature commonly structures analytics capabilities as descriptive (what happened), predictive (what is likely), and prescriptive (what should be done), emphasizing that the managerial value of analytics depends on how insights are integrated into planning processes rather than treated as standalone dashboards. Big-data and predictive-analytics scholarship further argued that analytics becomes strategically meaningful when it supports decisions that improve sustainability and service performance, linking data capability to operational outcomes through theory-driven constructs. For an AI-driven distribution planning framework, these ideas translate into measurable constructs such as "AI readiness" (organizational and technical ability to deploy analytics), "data quality" (accuracy, completeness, timeliness, consistency), and "use intensity" (how frequently predictions and optimization outputs are used in planning cycles). Reviews in logistics and supply chain management described machine learning adoption as expanding across planning tasks and highlighted the importance of aligning ML applications with the decision context, available data, and evaluation metrics that reflect operational realities (Waller & Fawcett, 2013). In humanitarian and emergency contexts, the same analytics logic is complicated by dynamic constraints, uncertainty, and socio-technical factors, where optimization models must reflect field realities rather than idealized assumptions. For this study, AI-driven distribution planning is positioned as an operational capability that can be measured in a cross-sectional design through Likert-scale constructs (e.g., perceived usefulness, trust in outputs, data availability, integration into workflows) and then linked statistically to access outcomes and equity profiles in the case community (Wang et al., 2016). The international relevance of this approach lies in its portability: many countries face similar challenges of limited last-mile infrastructure, unequal service coverage, and volatile demand, and many organizations are actively attempting to integrate predictive and prescriptive tools into distribution planning without consistent evidence on access impacts at community level (Zhang & Cui, 2021).

Prescriptive distribution planning connects AI and optimization through models that allocate limited resources across space and time. Humanitarian logistics studies developed integrated approaches where procurement, inventory, routing, and allocation decisions are solved jointly or sequentially to improve service under scarcity, and many models treat last-mile delivery as a vehicle routing–allocation problem with constraints such as time windows and split deliveries (Huang & Rafiei, 2019). Inventory-routing models extend this logic by explicitly modeling replenishment batches, consumption rates at dispensing sites, and service frequency, which are central to essential-goods continuity in underserved settings where periodic shortages are common. Technology-enabled routing extensions introduce heterogeneous fleets and alternative delivery assets, such as UAVs paired with trucks, to manage disrupted access and time variability, and recent work framed these as multi-objective problems balancing delivery efficiency and fulfillment fairness. Reinforcement learning approaches similarly model dynamic decision-making under travel-time uncertainty and demonstrate improvements in weighted objectives that combine delivered quantities, coverage of visited locations, and lateness penalties (Holguín-Veras et al., 2013). These contributions matter to essential-goods distribution planning because underserved communities often face stochastic travel times, limited road reliability, and high penalty for late delivery (Kalaitzi & Tsolakis, 2022). At the same time, "AI-driven" does not mean fully automated; many studies emphasize hybrid decision-making where algorithms generate candidate plans and humans validate feasibility and social acceptability, particularly when fairness constraints and local norms influence how allocations are perceived. When essential goods are involved, "criticality" becomes a planning dimension: items differ in urgency, substitution possibilities, and acceptable delay. This motivates analytic artifacts such as a "criticality matrix" that classifies goods by deprivation intensity and service priority, enabling the routing and allocation models to weight outcomes according to item criticality rather than treating all units equally. In the proposed thesis structure, these modeling traditions justify results sections that go beyond generic regression outputs and include study-specific profiles such as access equity mapping, criticality matrices, and AI readiness indices that translate model variables into interpretable community-level evidence (Kovács & Spens, 2007).

Equity measurement is a methodological cornerstone for any access-optimization study focused on underserved communities because average improvements can coexist with localized deprivation. Humanitarian logistics scholarship treats equity as both an ethical requirement and an operational risk factor because perceived unfairness can trigger conflict, noncompliance, and breakdown of distribution order in crisis contexts. Empirical and modeling work differentiates equity in delivered quantities, equity in arrival times, and equity in deprivation time—defined as the time gap between sequential deliveries—and shows that these measures are not interchangeable across delivery policies and time windows (Abdulla & Majumder, 2023; Lu et al., 2022; Rifat & Alam, 2022). The deprivation-cost literature supports equity-aware planning by specifying how deprivation accumulates and how convex deprivation functions increase the penalty for prolonged shortages, enabling objective functions to penalize long deprivation spells more strongly than short delays (Fahimul, 2023; Faysal & Bhuya, 2023). Yet, formal results show that minimizing total deprivation costs can still yield arbitrarily inequitable solutions when budget constraints and remote nodes create structural advantage for some locations, so inequity terms such as Gini-based penalties can be required for fairness control. In parallel, food bank distribution research provides a closely related lens for underserved-community logistics because it models equity and effectiveness under donated-supply scarcity and heterogeneous local capacity (Habibullah & Aditya, 2023; Hammad & Mohiul, 2023). Robust optimization studies formulated equity-effective distribution under capacity uncertainty and used real operational partnerships to ground model assumptions, treating "capacity to receive and distribute" as a contextual constraint rather than an abstract parameter (Haque & Arifur, 2023; Jahangir & Mohiul, 2023). Complementary research in operational research journals proposed vehicle routing–allocation heuristics and decision-support models specifically for food bank distribution networks and documented the practical role of intermediate delivery sites, shared transportation burden, and equitable cost-sharing across agencies. These studies align with essential-goods access optimization because they treat distribution as a service network for vulnerable populations, not a profit-maximizing supply chain (Manupati et al., 2021; Rashid et al., 2023; Akbar & Farzana, 2023). The implication for study design is that access equity can be operationalized as a construct with measurable indicators (e.g., perceived fairness of allocation, consistency of service frequency, timeliness experience) and can be analyzed quantitatively through descriptive profiles and inferential models linking AI-enabled planning practices to equity outcomes. In the results architecture you outlined, a dedicated "Access Equity Profile" section fits this literature by summarizing equity indicators and comparing subareas of the community, providing evidence that complements correlation and regression tables with interpretable, community-specific equity diagnostics (Mediavilla, 2022; Mostafa, 2023; Rifat & Rebeka, 2023).

AI effectiveness in distribution planning depends strongly on readiness and data quality, which are measurable constructs that bridge technical capability and operational impact. Supply chain analytics research emphasized that analytics maturity includes not only tools but also integration across processes, cross-actor data sharing, and governance practices that maintain data reliability under real constraints. Reviews in big data analytics for supply chain management described analytics as a capability spanning data acquisition, dissemination, and decision embedding, and positioned maturity as staged development from functional analytics to more agile and collaborative analytics capabilities (Jahangir & Hammad, 2024; Masud & Hammad, 2024; Steenbergen et al., 2023). The data-science and predictive-analytics literature similarly highlighted that value emerges when organizations translate data into planning decisions, which requires domain knowledge, quantitative skills, and process redesign, not only software adoption (Waller & Fawcett, 2013). In logistics and supply chain management, machine learning reviews identified recurring limitations tied to data availability, label quality, and evaluation mismatch, and these limitations are amplified in underserved contexts where records may be incomplete and field conditions shift rapidly (Holguín-Veras et al., 2013). For access optimization, these insights justify including "AI Readiness and Data Quality Index" as a results section because it transforms abstract capability into an empirical summary that can be compared across stakeholder groups in the case study (e.g., planners, field staff, local partners). Conceptually, readiness can include dimensions such as data infrastructure adequacy, staff competency, integration of analytics outputs into routine planning, and trust in model recommendations, while data quality can include timeliness, completeness, consistency, and bias risk in community coverage (Beamon & Balcik, 2008). The supply chain sustainability analytics agenda further supports measuring readiness through theory-driven constructs that connect analytics capabilities to operational outcomes, rather than treating analytics use as a single binary variable (Gutjahr & Fischer, 2018; Md & Praveen, 2024; Rifat & Rebeka, 2024). In essential-goods planning, data quality has direct operational meaning: errors in location data affect routing, errors in inventory records affect allocation feasibility, and delays in demand reporting affect forecast accuracy and replenishment timing. For a cross-sectional study using Likert-scale constructs, these readiness and quality dimensions can be analyzed with reliability testing, descriptive statistics, correlation matrices, and regression modeling to quantify how AI readiness and data quality relate to access outcomes and equity perceptions within the community (Sai Praveen, 2024; Shehwar & Nizamani, 2024; Steenbergen et al., 2023).

A mixed methods framing adds methodological legitimacy when a study integrates community context with quantitative measurement of planning constructs, even when the core empirical design is quantitative, cross-sectional, and case-study based. Evidence-based humanitarian logistics research proposed structured mixed methods methodologies that connect field insights to optimization model formulation, explicitly addressing the risk that models become detached from real constraints and stakeholder priorities (Azam & Amin, 2024; Waller & Fawcett, 2013). This perspective aligns with access optimization in underserved communities because qualitative inputs can define what "access" means locally (e.g., acceptable waiting time, preferred delivery points, perceived fairness) while quantitative measurement evaluates how planning practices and AI use correlate with outcomes across respondents in the case setting (Holguín-Veras et al., 2016). In optimization-oriented humanitarian logistics, recent work also framed multi-objective design as necessary for capturing simultaneous goals of efficiency and equity, particularly when alternative delivery assets and uncertain conditions shape feasible policies. Public-health distribution experiences during COVID-19 provided additional operational grounding for last-mile complexity, where distribution depends on coordination across sectors and the "last mile" includes organizational capacity, not only transportation distance. Vaccine distribution modeling studies showed that cold-chain requirements, limited doses, and equitable allocation constraints must be managed jointly to maintain service coverage across geographic and population segments. While essential goods extend beyond vaccines, these findings illustrate how criticality, storage constraints, and prioritization rules shape access optimization (Huang & Rafiei, 2019). In the context of this thesis, the case study can be framed as a bounded distribution ecosystem where an organization (or network of partners) plans essential goods delivery under constraints of resources, data, and community geography. The cross-sectional survey provides quantifiable indicators of constructs such as perceived access, distribution reliability, equity, AI readiness, and data quality, while the case context provides the operational narrative for interpreting patterns in descriptive and inferential results (Kalaitzi & Tsolakis, 2022). The research questions and hypotheses can be anchored in the literature that links analytics capability and planning quality to service outcomes, and the results structure you designed (equity profile, criticality matrix, AI readiness/data quality index) operationalizes these constructs into study-specific evidence that supports trustworthiness through triangulation of metrics, not by adding speculative claims (Wassenhove, 2006).

This study is structured around a set of objectives that translate the broad challenge of essential-goods access in underserved communities into measurable constructs, testable relationships, and empirically verifiable outcomes within a quantitative, cross-sectional, case-study context. The first objective is to operationalize "access optimization" in a way that reflects real conditions experienced by underserved populations by measuring access as a multi-dimensional outcome that includes perceived availability of essential goods, reliability and consistency of supply, timeliness of delivery, affordability-related burden, and fairness of service coverage across different locations within the case setting. The second objective is to identify and quantify the dominant access barriers and distribution constraints in the selected community by developing a structured profile of logistical and contextual limitations, such as travel time variability, stockout frequency, infrastructure limitations, and coordination gaps between stakeholders involved in distribution. The third objective is to measure AI-driven distribution planning capability as an organizational and operational construct, capturing the degree to which forecasting, routing support, allocation logic, and inventory visibility tools are present and embedded in routine planning processes, including how frequently such tools are used, how trusted their outputs are, and whether the system supports data sharing and integration across actors. The fourth objective is to evaluate the readiness conditions that enable or restrict AI-supported planning by quantifying data quality and integration characteristics, staff and process readiness, and the stability of information flows that feed planning decisions. The fifth objective is to examine the statistical relationships between AI-driven planning capability, planning effectiveness, readiness conditions, and access optimization outcomes using descriptive statistics to establish baseline patterns, correlation analysis to identify associations among constructs, and regression modeling to estimate the predictive influence of AI capability and readiness on access outcomes while accounting for key contextual constraints. The sixth objective is to strengthen the credibility and practical relevance of the findings by producing study-specific evidence artifacts that connect quantitative results to operational decision needs, including an access equity profile that demonstrates whether access gaps are systematically distributed across the case-study area, an essential goods criticality matrix that ranks goods by perceived urgency and scarcity risk to support prioritization decisions, and an AI readiness and data quality index that clearly indicates whether observed performance outcomes occur within conditions supportive of AI-enabled planning. Together, these objectives provide a coherent path from measurement to modeling that supports a rigorous evaluation of how AI-driven distribution planning relates to improved access optimization for essential goods in underserved communities.

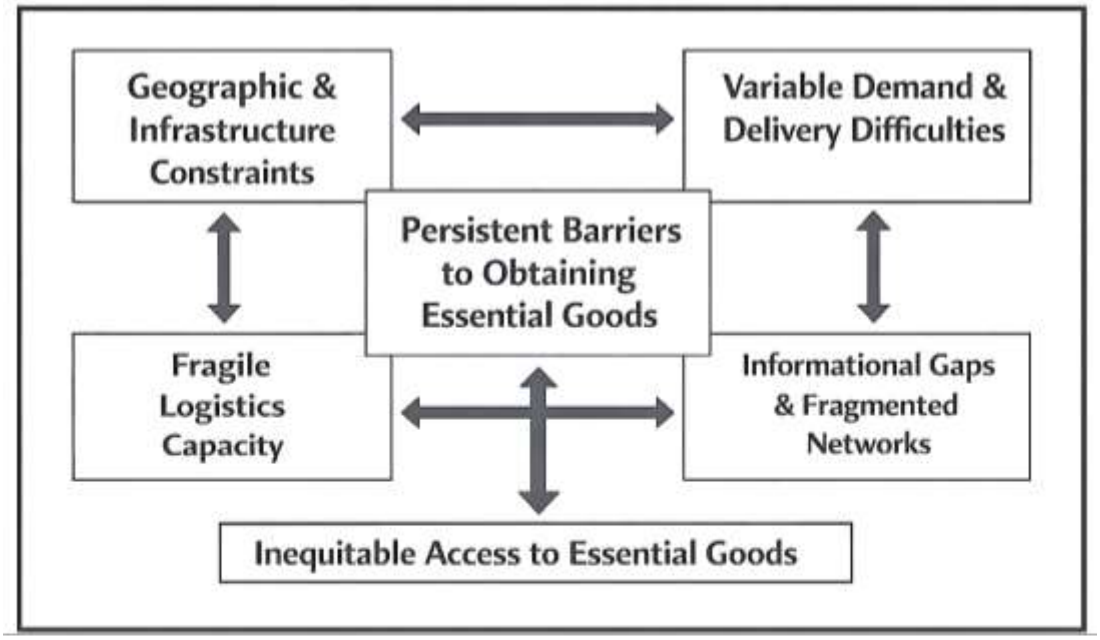
LITERATURE REVIEW

The literature on AI-driven distribution planning for essential goods in underserved communities spans humanitarian logistics, last-mile distribution, supply chain analytics, equity-focused operations research, and technology adoption in resource-constrained environments. At its core, this body of work examines how distribution systems can be designed and managed to improve access outcomes such as availability, timeliness, reliability, and fairness when demand is uncertain, infrastructure is limited, and coordination across stakeholders is complex. Studies in humanitarian and relief logistics provide foundational insights into essential-goods delivery under scarcity, emphasizing that distribution decisions are shaped by urgency, limited transportation capacity, fragmented information, and the need to balance efficiency with equitable coverage. Related operations research contributions extend these insights by formalizing access-oriented objective functions and constraints, introducing equity-sensitive metrics, deprivation-based penalties, and multi-objective formulations that represent trade-offs between cost, speed, and fairness across locations. Alongside these modeling traditions, supply chain analytics research explains how descriptive, predictive, and prescriptive analytics can strengthen planning by improving demand estimation, inventory visibility, and routing decisions, particularly when data are integrated into routine decision cycles rather than treated as isolated tools. The rapid growth of machine learning applications in logistics has expanded the toolkit for forecasting demand, identifying risk hotspots, classifying service needs, and supporting route planning under uncertainty; however, the value of these techniques depends on data quality, algorithmic trust, and organizational readiness to embed outputs into planning processes. In underserved communities, these conditions are rarely uniform, making it essential to incorporate readiness and data-quality considerations when evaluating the practical impact of AI-driven planning. Technology adoption frameworks further contribute by explaining how technological capability interacts with organizational capacity and environmental constraints, providing a structured lens to interpret why similar tools may produce different outcomes across contexts. Collectively, this literature supports an integrated view of access optimization as a socio-technical problem: access outcomes emerge from the interaction of analytical capability, operational decision rules, infrastructure constraints, and stakeholder coordination. Building on these foundations, the present study positions access optimization as a measurable outcome and AI-driven distribution planning as a capability that can be operationalized through survey constructs and tested statistically within a case-study setting, while also incorporating study-specific evidence artifacts—such as an access equity profile, essential goods criticality matrix, and AI readiness/data quality index—to strengthen interpretability and decision relevance.

Essential-Goods Access and Last-Mile Distribution Challenges

Essential-goods distribution in underserved communities is commonly framed as an access problem produced by the interaction of geography, purchasing power, information gaps, and fragile logistics capacity. In many low-income neighborhoods and remote settlements, residents face limited retail density, constrained transportation options, and intermittent availability of basic items, which together create persistent last-mile conditions even outside formal disasters. Access is therefore not only the presence of supply in a region, but the practical ability of households to obtain required goods in adequate quantity and quality, within acceptable time, cost, and travel burden, and with fair service levels across locations. From an operations viewpoint, these conditions translate into variable demand, high delivery friction, and limited buffering inventory, which increase the penalty of planning errors and amplify the consequences of small disruptions. Case-based evidence from supply-side distribution initiatives shows that access can be constrained less by total supply and more by ordering rules, handling capacity, delivery frequency, and minimum-order economics that small outlets cannot meet. A program designed for small retailers illustrates how coordinated ordering and delivery, supported by targeted infrastructure, can reduce waste risk and transaction costs while increasing availability of perishable essentials in underserved areas (DeFosset et al., 2018). Such findings motivate treating access optimization as a measurable outcome of distribution design rather than as a purely behavioral or consumer-choice phenomenon. For the present study, this stream of literature supports modeling access as a multi-dimensional construct capturing perceived availability, reliability, timeliness, and neighborhood-level equity, assessed through structured survey items in a cross-sectional case setting. Importantly, underserved contexts often involve mixed distribution channels, including formal retailers, informal vendors, and community organizations, so the effective supply network is fragmented and difficult to coordinate. Accordingly, measurement must capture both system performance and user experience, allowing statistical tests to connect planning capability with lived access outcomes in this study.

Figure 2: System-Level Challenges in Essential-Goods Distribution for Underserved Communities



Research on humanitarian and high-constraint distribution provides transferable principles for essential-goods planning in underserved settings, because both domains require allocating scarce transport and inventory across multiple demand points under time pressure. Modeling work emphasizes that the objective function chosen for distribution planning strongly shapes who gets served first, how quickly, and in what quantities, which matters when equity is a stated goal rather than a secondary consideration. A multi-objective relief-delivery formulation demonstrates this logic by simultaneously minimizing cost and travel time while maximizing a fairness-oriented satisfaction measure, showing how planners can encode service balance directly into optimization criteria (Tzeng et al., 2007). Although the present study is not an emergency-response optimization project, the same insight applies to routine essential-goods distribution: if planning systems optimize only efficiency proxies, underserved micro-areas may remain systematically under-served. Route design and allocation decisions also depend on how equity is defined and measured, since fairness can refer to equal quantities, comparable waiting times, or reduced disparity in service levels across neighborhoods. Analytical relief-routing models comparing efficiency, efficacy, and equity show that equity-aware metrics can produce materially different routes than cost-minimizing vehicle routing, while remaining implementable under realistic constraints (Huang et al., 2012). For AI-driven planning, this implies survey items must capture whether tools use equity metrics and whether decisions change when inequities are flagged. Cross-sectional case evidence can then test whether higher perceived AI capability correlates with better access outcomes and whether readiness and data quality strengthen that relationship, consistent with a socio-technical view of planning performance. Finally, regression specifications should control for structural constraints such as transport capacity, network reliability, and lead-time volatility, so estimated AI effects reflect decision quality. This improves interpretability for policymakers, practitioners, and community stakeholders.

Beyond individual routing models, the broader relief-distribution network literature clarifies how performance emerges from the configuration of depots, inventory positioning, information flows, and coordination rules across actors. Systematic synthesis of relief distribution network studies indicates that many approaches integrate location decisions, inventory policies, and transportation planning, and that assumptions about demand uncertainty, network disruption, and service priorities directly influence achievable equity and responsiveness (Anaya-Arenas et al., 2014). For essential-goods access in underserved communities, the practical analogue is the community-level network of sourcing points, micro-distribution hubs, informal vendors, and delivery services that collectively determine whether households experience stable access or repeated shortages. Because these networks often rely on fragmented data, the credibility of AI-driven distribution planning depends on the availability of timely, interoperable, and locally granular information about demand, stock levels, and delivery constraints. Humanitarian logistics review work further emphasizes that decision-support tools create value only when embedded in routines and supported by organizational capability, including skilled personnel, standardized data practices, and collaboration mechanisms across organizations (Leiras et al., 2014). This aligns with treating AI readiness and data quality as central constructs rather than background conditions, since weak data pipelines can cause predictions and optimization outputs to be ignored, overridden, or misapplied. An implication for measurement is that perceived trust in model outputs should be separated from mere tool availability, because communities may experience improved access only when organizations act on recommendations in allocation, replenishment, and routing decisions. Taken together, these insights justify reporting results with dedicated evidence artifacts—an access equity profile, a criticality matrix for prioritizing essential goods, and a readiness and data-quality index—so statistical findings are interpretable in the operational language of the case context. Such artifacts help connect survey-based regression effects to concrete distribution redesign opportunities at neighborhood scale directly.

Indicators for Essential-Goods Distribution

Access optimization in essential-goods distribution is most credible when it is defined through measurable indicators that capture how people actually experience “getting” essential items, not only how efficiently a network moves inventory. In the access literature, a practical starting point is to treat access as a combined function of supply availability, demand pressure, and the impedance that separates households from supply points (distance, travel time, and transport constraints). Indicator families used for spatial access often quantify “potential access” by linking where goods are stocked (or distributed) to where people live, then discounting the linkage by travel-time friction; a widely used example is the enhanced two-step floating catchment area (E2SFCA) method, which improves the basic catchment concept by applying distance-decay weights within the catchment so that nearer supply contributes more strongly than farther supply (Luo & Qi, 2009). Although originally popular in health-access measurement, the same logic generalizes to essential goods: distribution nodes, temporary hubs, and mobile delivery points can be treated as supply locations, while population zones represent demand, allowing the study to compute access scores that are interpretable at neighborhood scale. When access is conceptualized as “reachability of opportunities,” indicators can be expressed as the number (or share) of essential-good opportunities reachable within a time budget, or as a weighted opportunity score that reflects destination attractiveness and connectivity conditions. An example from last-mile evaluation demonstrates how accessibility-based scoring can be constructed using rich location and travel-time data, producing a continuous performance measure that reveals spatial disparity and clustering of low-access areas (Chen et al., 2021). For this thesis, such indicator logic supports converting "access optimization" into measurable outcomes suitable for a cross-sectional case study: perceived availability and continuity (stockout frequency and replenishment consistency), time burden (waiting time and travel time), reliability (probability of on-time receipt), and coverage (whether all subareas receive comparable service frequency). These outcomes can be measured via Likert-scale items and summarized descriptively, while also being represented through a small set of community-level indices to make the results operationally interpretable.

Because indicators define what is treated as success, access optimization requires indicator discipline: the same distribution system can appear "better" under a cost or speed metric while remaining inequitable under an opportunity or reliability metric. Planning research shows that accessibility is often invoked as a goal but inconsistently translated into performance indicators, with many institutions still substituting mobility measures (such as congestion reduction) for true access measures (such as opportunities reachable), which reduces accountability and limits cross-case comparability (Boisjoly & El-Geneidy, 2017). Translating this lesson into essential-goods distribution implies that "on-time delivery rate" or "average route distance" alone is insufficient for underserved communities, because these metrics can improve while some zones remain persistently under-served. A more defensible indicator set combines (1) service effectiveness (fill rate, stockout incidence, order completeness), (2) service timeliness (delivery lead time, delay frequency, schedule adherence), (3) service reliability (consistency of supply across cycles), and (4) service coverage (share of households/areas reaching minimum service thresholds). To ensure indicators remain grounded in stakeholder needs, humanitarian performance measurement research emphasizes that logistics metrics should reflect beneficiaries and other key stakeholders, not only internal efficiency; customer-oriented frameworks operationalize performance across dimensions that include responsiveness, dependability, and perceived service adequacy (Schiffling & Piecyk, 2014).

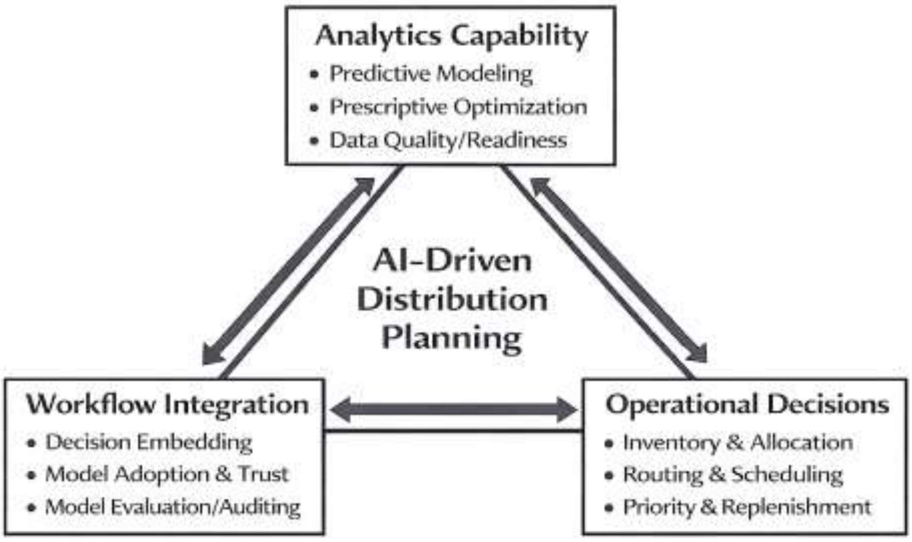
Figure 3: Access Optimization Metrics and Equity-Oriented Indicators for Essential-Goods Distribution

In the context of this study, that principle directly supports combining objective-like operational proxies (e.g., reported stockout frequency, reported delivery delays, reported delivery frequency) with perception-based constructs (e.g., perceived fairness, perceived availability, perceived reliability) gathered through a structured instrument. This mixed indicator logic strengthens construct validity because it reduces the risk that the study measures only "what is easy" rather than "what matters" for access optimization. It also aligns with your results architecture: descriptive statistics establish baseline access conditions; correlation analysis identifies which access dimensions move together; regression modeling then estimates how AI-driven planning capability and readiness predict access outcomes while controlling for case-specific constraints. Equity-oriented indicators are essential because access is distributive: averages can rise while inequality persists, and underserved communities are defined by precisely these uneven distributions of service and opportunity. Equity can be represented as differences in delivery time, differences in quantity received, differences in stockout experience, or differences in perceived service fairness across subareas, and each form of inequity requires a metric that is transparent and interpretable for decision-makers. One approach is to adopt inequality indices (Gini-like logic) as reporting tools so that planners can quantify how unevenly resources or service benefits are distributed across sectors or locations. For disaster-response accountability, the PEARL approach formalizes a Gini-like index and standardized reporting to compute and communicate inequity across sectors, strengthening transparency and enabling comparisons across events and categories of aid (Carlson et al., 2016). While PEARL was developed for disaster funding and sector reporting, its core idea is transferable: access equity can be tracked as an inequity index computed over neighborhood-level access scores, delivery frequency, or stockout incidence, and then paired with threshold-based equity checks (e.g., minimum service levels for all zones). This is exactly the type of evidence that can make your "Access Equity Profile" results section study-specific and trustworthy: it shows not only whether access improves but whether disparities narrow. In addition, equity should be tied to "criticality" because not all essential goods impose the same welfare loss when delayed; therefore, equity reporting can be stratified by a criticality matrix so that inequities in high-criticality goods (e.g., medicines, infant nutrition) are not hidden within aggregate totals. Finally, equity indicators should be paired with readiness indicators: if an AI system is applied in a low-quality data environment, it may inadvertently amplify existing blind spots, so interpreting equity outcomes requires reporting AI readiness and data quality alongside equity metrics. Together, accessibility metrics, stakeholder-oriented service indicators, and equity indices form a coherent measurement foundation for your quantitative case study, enabling descriptive, correlational, and regression analyses to be interpreted as evidence about access optimization rather than as isolated statistics.

AI-Driven Distribution Planning in Supply Chains

AI-driven distribution planning in supply chains can be understood as the integration of data-intensive prediction and algorithmic decision support into the routines that determine how inventory is positioned, how demand is anticipated, and how deliveries are executed across time and space. In distribution-intensive systems, planning quality depends on the ability to convert heterogeneous data—sales histories, inventory records, mobility constraints, supplier reliability, and service feedback—into actionable schedules and allocation rules that improve service outcomes under uncertainty. This has led the supply chain field to treat analytics not merely as a technical add-on, but as a capability that must be developed and embedded through processes, governance, and cross-functional alignment. A central theme in this literature is that AI value becomes visible when analytics outputs are translated into operational actions such as route changes, replenishment adjustments, safety stock recalibration, and priority rules for scarce items. Empirical research has therefore examined how big data and predictive analytics connect to supply chain and organizational performance, emphasizing that predictive insights must be timely and decision-relevant to influence actual planning outcomes such as responsiveness, service reliability, and resource utilization (Gunasekaran et al., 2017). In distribution planning specifically, the practical benefit of AI emerges when forecasts reduce demand uncertainty at local granularity and when decision support reduces the friction of repeatedly updating plans across many destinations. For essential goods distributed to underserved communities, these issues are magnified because demand may vary sharply across neighborhoods and periods, and because operational constraints—fleet limitations, infrastructure variability, and data gaps—make planning errors more costly in terms of access. As a result, AI-driven distribution planning is best conceptualized as a socio-technical capability that includes both the analytical core (models, data, and metrics) and the organizational mechanisms that operationalize recommendations. This framing aligns with a measurement approach that uses survey constructs to capture the presence, intensity, and perceived usefulness of AI-supported forecasting, inventory visibility, and routing support, and then links these constructs statistically to access optimization outcomes in the case-study setting. A second core stream focuses on how organizations build analytics capability and how capability must align with strategy and decision processes to produce measurable improvements. Evidence indicates that analytics capability is multi-dimensional, including technological resources (data infrastructure, systems integration), human resources (skills, analytical literacy), and management resources (process redesign, leadership support, performance measurement). Work on big data analytics capability and strategic alignment highlights that capability alone does not automatically translate into performance; performance improvements depend on whether analytics is aligned with the organization's operating strategy and whether planning workflows are redesigned so that analytics outputs are used consistently in decisions rather than being treated as optional reports (Akter et al., 2016).

Figure 4: Analytics Capability and Workflow Integration in AI-Driven Distribution Planning



In distribution planning, this alignment challenge is visible in how route planners, inventory managers, and field coordinators coordinate around a shared "single version of truth," and whether the organization has mechanisms for validating, adopting, and auditing model outputs. Editorial synthesis in logistics and supply chain management similarly emphasizes that analytics must be embedded into planning cycles, supported by governance and data-sharing, and evaluated through relevant operational performance metrics rather than through abstract technical accuracy alone (Fosso Wamba et al., 2018). For underserved-community distribution, these insights justify treating "AI readiness" and "data quality/integration" as central explanatory constructs rather than background variables, because weak readiness can prevent analytics from influencing delivery schedules and allocation decisions even when software exists. This is especially important in cross-sectional case study designs, where measured outcomes depend on what organizations actually do in routine planning rather than what they intend to do. Therefore, a rigorous operationalization distinguishes between tool availability, degree of integration into workflows, and decision impact, allowing subsequent correlation and regression analyses to estimate which aspects of AI capability most strongly relate to access optimization outcomes.

A third strand addresses how AI and advanced analytics inform prescriptive decision-making in distribution planning, while also recognizing the need for interpretability and trust when recommendations affect high-stakes service outcomes. In operations management, big data analytics has been framed as a driver of operational decision improvement, connecting data intensity with the ability to support faster and more accurate decisions across planning horizons and across uncertain environments (Choi et al., 2018). In distribution contexts, this supports the view that predictive models (for demand, delays, and disruption risk) and prescriptive models (for routing, allocation, and scheduling) are complementary components of AI-driven planning. Yet, the literature also shows that predictive accuracy is not the only determinant of practical adoption; decision-makers must understand and trust model outputs to act on them, and this requirement becomes more salient when decisions affect vulnerable populations and when operational errors can widen inequities. Research on supply chain risk prediction using machine learning demonstrates this trade-off by showing that highly accurate models may be less interpretable, while more interpretable approaches can offer actionable explanations that help practitioners intervene and adjust plans, especially when the goal is to prevent delivery delays and service failures (Baryannis et al., 2019). For essential goods distribution in underserved communities, interpretability is particularly relevant because planners often must justify prioritization and routing decisions to stakeholders, and because data can contain systematic blind spots that, if unrecognized, may reinforce unequal service patterns. This literature supports including study-specific reporting elements—such as an AI readiness and data-quality index and an access equity profile—because these artifacts provide context for interpreting regression effects and for understanding whether observed "AI capability" is likely to be producing meaningful operational decisions or merely reflecting nominal technology presence. Within the thesis, these insights position AI-driven distribution planning as an integrated capability linking data, models, workflow embedding, and trust, which can be empirically examined through validated constructs and statistical modeling in the selected case setting.

Technology–Organization–Environment (TOE) Framework

The Technology–Organization–Environment (TOE) framework is adopted as the guiding theoretical lens for this thesis because it explains organizational-level technology-enabled change through three complementary contexts that jointly shape adoption and use outcomes: (i) the technological context (availability, characteristics, and fit of the technology and data resources), (ii) the organizational context (structure, resources, governance, skills, and managerial support), and (iii) the environmental context (external pressures, partnerships, policy conditions, and ecosystem constraints). In TOE, "adoption" is not treated as a purely technical choice; it is an organizational decision and capability-building process that depends on whether the technology can be integrated into decision routines and whether external conditions enable sustained operation and scaling. Baker's formulation of TOE emphasizes that these contexts offer a flexible taxonomy for operationalizing adoption factors in a way that fits the studied domain, which is valuable for AI-driven distribution planning where data pipelines, planning workflows, and stakeholder relationships differ widely across settings (Baker, 2011). In supply-chain technology contexts, TOE has been repeatedly used to explain why similar tools (e.g., visibility, automation, analytics) generate different performance outcomes across organizations, because technological readiness and organizational capacity vary and external dependencies are often decisive. For example, empirical adoption research on RFID in manufacturing demonstrates that firm-level adoption decisions can be modeled through TOE factors and validated statistically, reinforcing TOE's suitability for studying operational technologies that affect planning, coordination, and execution (Wang et al., 2010).

For essential-goods access optimization, TOE provides a defensible structure for linking AI-driven distribution planning to access outcomes because the capability to plan with AI depends simultaneously on technological inputs (data quality, interoperability, model usability), organizational inputs (skills, governance, leadership backing), and environmental inputs (partner data-sharing, community logistics ecosystem, regulatory constraints). Accordingly, TOE is applied here not as a generic "adoption theory," but as a mechanism for building measurable constructs that map directly onto distribution planning performance and equity-centered access outcomes within the case-study community. Within this study, the TOE contexts are operationalized into measurable constructs that can be captured using Likert-scale items and then tested through descriptive statistics, correlation analysis, and regression modeling.

Figure 5: TOE Framework Linking AI-Driven Planning Capability to Access Optimization

The technological context is represented through (a) AI Planning Capability (e.g., demand forecasting support, routing/dispatch decision support, allocation logic, inventory visibility), and (b) Data Quality & Integration (e.g., timeliness, completeness, consistency, interoperability, and local granularity of demand/stock/delivery data). The organizational context is represented through (c) Planning Process Maturity (standardization of replenishment and routing cycles, exception-handling routines, performance monitoring cadence), (d) Human & Managerial Readiness (analytical skills, training availability, top-management support, and perceived decision authority to act on model outputs), and (e) Governance & Trust (auditability, transparency of decision rules, perceived reliability of AI outputs, and accountability arrangements). The environmental context is represented through (f) Ecosystem Collaboration Pressure/Support (partner coordination, data-sharing agreements, supplier reliability), and (g) Policy/Infrastructure Constraints (transport reliability, connectivity limitations, and local rules affecting distribution operations). This TOE-aligned decomposition is consistent with TOE-based evidence showing that adoption determinants often cluster into technology readiness, organizational support/structure, and external pressures, while remaining adaptable to domain specifics (Oliveira et al., 2014). It also aligns with calls to refine TOE into clearer factor taxonomies that reflect task demands and the realities of enterprise adoption, particularly when outcomes depend on workflow embedding rather than nominal tool presence (Awa et al., 2017). Because the thesis evaluates access optimization in underserved communities, the TOE logic is extended from “adoption intention” to “embedded use that changes operational decisions,” meaning the measurement focuses on whether AI actually influences replenishment, allocation, and routing choices, and whether the organization has the data and authority to implement those choices consistently under real constraints.

To connect TOE constructs to the thesis outcomes in a single, reusable model, the study uses a regression-based specification that treats Access Optimization (AO) as the dependent variable and TOE-aligned capability/readiness factors as predictors. The primary formula applied across hypotheses is a multiple linear regression model (with standardized construct scores derived from Likert items): $AO = \beta_0 + \beta_1(AI\_CAP) + \beta_2(DATA\_Q) + \beta_3(ORG\_READY) + \beta_4(ENV\_SUPPORT) + \beta_5(CONSTRAINTS) + \varepsilon$.

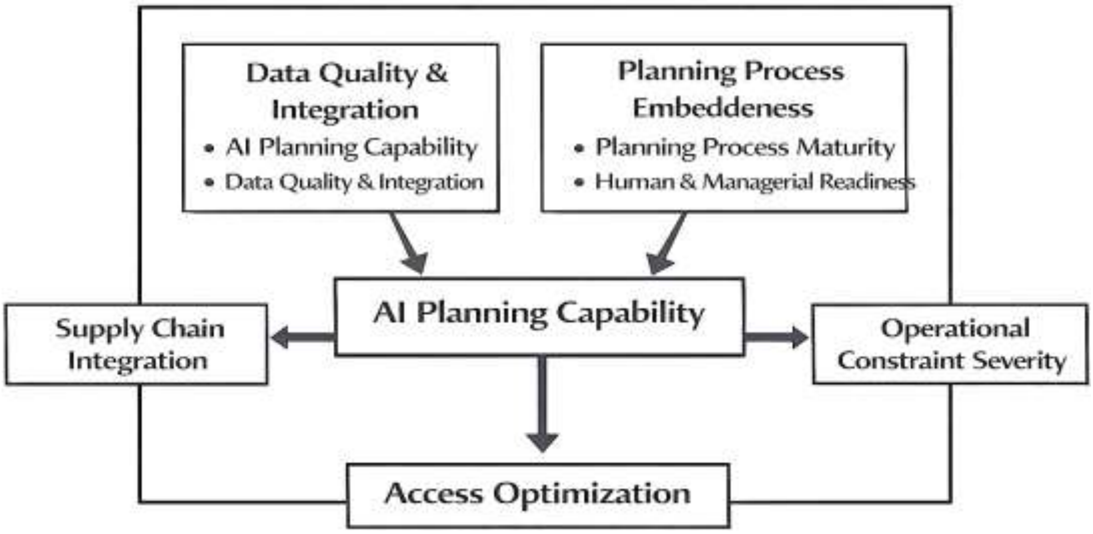
Here, AO is measured as a composite of perceived availability, reliability/continuity, timeliness, affordability burden, and fairness of coverage across subareas in the case community; AI_CAP captures perceived AI-driven planning capability; DATA_Q captures data quality and integration; ORG_READY captures skills, leadership support, and process maturity; ENV_SUPPORT captures ecosystem collaboration and enabling external conditions; and CONSTRAINTS captures persistent structural barriers (e.g., transport reliability limitations) that should be controlled to avoid overstating technology effects. This model is “best” for the whole study because it aligns with your stated analysis plan (descriptives → correlations → regressions) and directly maps TOE constructs onto testable hypotheses about access outcomes in one coherent equation. To strengthen study-specific trustworthiness, the thesis can also compute an AI Readiness & Data Quality Index (ARDQI) for reporting and robustness checks using a simple weighted composite that remains interpretable for stakeholders: $ARDQI = (w_1 \cdot DATA\_Q + w_2 \cdot AI\_CAP + w_3 \cdot ORG\_READY) / (w_1 + w_2 + w_3)$, where weights can be set equally ($w_1 = w_2 = w_3 = 1$) unless the case context justifies differential weighting. This TOE-to-regression operationalization is consistent with empirical TOE adoption modeling in analytics-intensive contexts and supports clear hypothesis testing about which context(s) most strongly predict improved access optimization (Maroufkhani et al., 2020).

Conceptual Framework and Hypotheses Development

Building on the TOE lens established in this thesis, the conceptual framework in this subsection translates the theory into a testable, case-study–specific model that links AI-driven distribution planning to essential-goods access optimization in underserved communities. The framework treats Access Optimization (AO) as the focal outcome and models it as a multi-dimensional construct reflecting perceived availability, delivery timeliness, supply reliability/continuity, affordability burden (as a practical access barrier), and perceived fairness of coverage across subareas. In parallel, the framework defines AI Planning Capability (AIPC) as the degree to which planning activities (forecasting, replenishment, allocation, and routing) are supported by data-driven tools that influence actual operational decisions rather than merely producing dashboards. Two enabling mechanisms are positioned as core antecedents of effective AIPC: Data Quality & Integration (DQI) and Planning Process Embeddedness (PPE). DQI captures completeness, timeliness, consistency, and interoperability of demand, inventory, and delivery data; this emphasis is consistent with the argument that analytics-driven decisions can only be as reliable as the underlying data production and monitoring process (Hazen et al., 2014). PPE captures whether analytics outputs are routinely used in planning cycles, exception handling, and performance review, and it is grounded in the broader insight that data science and predictive analytics must be routinized within supply chain decision routines to deliver operational value (Schoenherr & Speier-Pero, 2015). In addition, Supply Chain Integration (SCI) is positioned as a bridging construct because information and material-flow integration with partners supports visibility and coordinated execution, which are essential for reaching underserved zones consistently (Prajogo & Olhager, 2012). Finally, Operational Constraint Severity (OCS) is modeled as a contextual control factor (e.g., transport unreliability, infrastructure constraints, and variability in replenishment lead times) because these conditions shape what access levels are feasible and help avoid overstating technology effects. This conceptual structure directly supports the thesis objective of statistically testing whether higher AI-driven planning capability—under adequate data quality, embedded processes, and integration—predicts improved access optimization outcomes in the case community.

To ensure that the conceptual framework is operationally measurable and statistically consistent with the study design, constructs are translated into survey-based indices using a uniform scoring rule suitable for Likert five-point data. The primary scoring formula applied throughout the thesis is the composite construct score computed as the mean of item responses: $Score(X) = (\Sigma_i x_i) / k$, where k is the number of items for construct X (e.g., AIPC, DQI, PPE, SCI, AO). This approach supports interpretability and comparability across constructs and aligns with the study's descriptive, correlational, and regression workflow. To strengthen case-specific credibility, the framework introduces a single index used consistently in the Results section: the AI Readiness and Data Quality Index (ARDQI), computed as $ARDQI = (AIPC + DQI + PPE) / 3$, where equal weights preserve transparency unless the case evidence strongly supports differential weighting. This index is justified because operational execution depends simultaneously on decision-support availability, input-data reliability, and workflow embedding, which collectively determine whether AI can reduce planning error and improve service consistency.

Figure 6: Conceptual Model Linking AI Planning Capability to Access Optimization



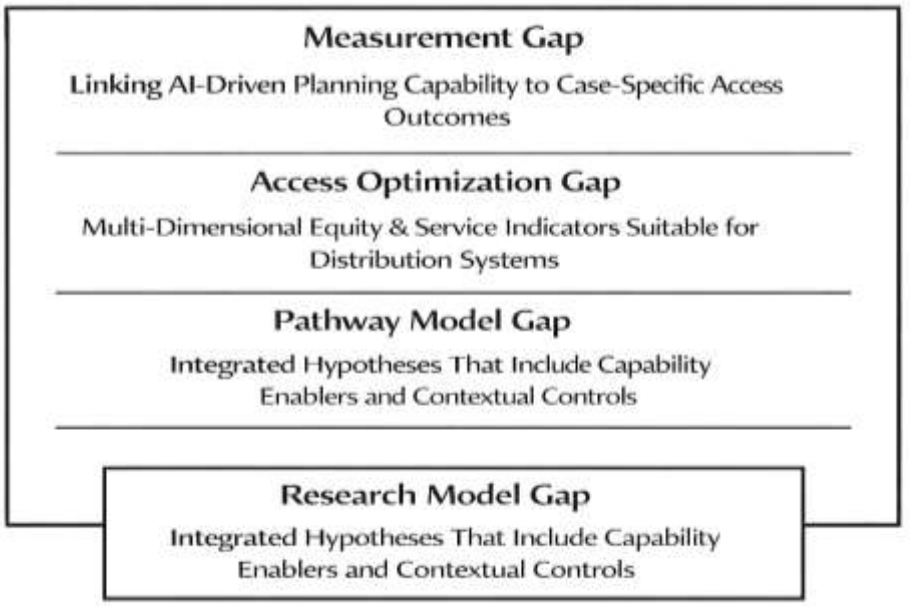
The framework also incorporates a practical information-sharing mechanism because distribution performance depends on coordination and the flow of reliable signals (demand, inventory, and delivery status) across actors. Simulation evidence shows that information sharing can significantly effect on-time delivery and total cost outcomes, reinforcing why the framework treats integration and sharing as performance-relevant rather than optional (Hall & Saygin, 2012). In hypothesis terms, the model expects positive associations between AIPC and AO, between DQI and AO, and between PPE and AO, while also expecting SCI to amplify these relationships by improving coordination. OCS is expected to show a negative association with AO, reflecting the role of persistent barriers that constrain distribution performance even when planning capabilities improve.

The statistical expression of the conceptual framework is designed to be reused consistently across hypothesis testing, ensuring that the study remains coherent from theory to measurement to modeling. The central estimation model is a multiple regression specification aligned with the framework: $AO = \beta_0 + \beta_1(AIPC) + \beta_2(DQI) + \beta_3(PPE) + \beta_4(SCI) + \beta_5(OCS) + \varepsilon$. This single equation is the "best-fit" formula for the whole study because it supports (i) direct hypothesis testing of AI-driven planning effects on access outcomes, (ii) inclusion of readiness and integration mechanisms as explanatory predictors, and (iii) control for constraint severity to strengthen internal validity in a cross-sectional case context. To make results "trustworthy" for this specific topic, the framework also prespecifies two case-tailored outputs that connect statistical findings to distribution decisions: an Access Equity Profile and an Essential Goods Criticality Matrix. The Access Equity Profile summarizes whether access outcomes are evenly distributed across subareas using an inequality-style metric, reported as a secondary diagnostic rather than a replacement for regression. The Essential Goods Criticality Matrix ranks goods by perceived urgency and shortage risk to show whether AI-driven planning capability is associated with improved access particularly for high-criticality goods. Finally, the framework recognizes that AI-driven analytics capability may not deliver benefits if organizational culture and process context are not supportive; evidence in humanitarian-style operations indicates that AI-driven analytics capability can influence agility and resilience but is sensitive to organizational conditions and operational realities (Dubey et al., 2019). Taken together, this conceptual framework provides a TOE-aligned, measurable, and testable structure that guides your correlation and regression analyses while producing decision-relevant, study-specific result artifacts.

Research Gap and Synthesis Leading to the Hypotheses

The literature reviewed in the preceding sections establishes that essential-goods distribution in underserved communities is shaped by complex interactions among logistics constraints, information quality, and equity expectations, yet clear empirical gaps remain regarding how AI-enabled distribution planning translates into measurable improvements in access optimization at community level. A dominant limitation is that many studies are either highly technical (optimization- or algorithm-centered) or highly contextual (qualitative and descriptive of access barriers), with fewer studies providing a direct, statistically testable bridge between organizational AI planning capability and community-level access outcomes within a single, real-world case study. While optimization-focused research produces valuable prescriptions, it often relies on stylized assumptions such as complete demand visibility, stable travel-time estimates, or rational implementation capacity, which are rarely present in underserved environments. In contrast, field-oriented studies on distribution barriers frequently document access limitations but do not measure whether specific AI-driven planning capabilities and readiness conditions predict improvements in service reliability, perceived availability, or equity of coverage. This separation results in a literature gap where the evidence is rich in concepts and models but less robust in causal-like empirical testing under realistic constraints. Additionally, while humanitarian logistics literature has advanced significantly, its insights are not always operationalized into scalable metrics that organizations can measure consistently in routine essential-goods distribution systems outside disaster-response windows. Systematic reviews emphasize that the humanitarian logistics field includes diverse methods and contexts, yet consistency in measurement and evaluation remains a known challenge, which reduces comparability across studies and weakens the ability to generalize lessons into practice (Kunovjanek & Wankmüller, 2021). In AI-enabled planning research, further gaps appear around implementation capacity and governance: a technology may exist, but its operational impact depends on data integration and sustained usage. This is particularly important in underserved settings where planning decisions must be made under fragmented stakeholder ecosystems and inconsistent data pipelines. Even in broader supply chain contexts, scholars have noted that the managerial and governance dimensions of AI adoption can be as decisive as algorithm choice, and that empirical evaluation must account for institutional and operational embeddedness rather than treating AI as a stand-alone technical asset (Barratt & Oke, 2007). Therefore, the present study positions the research gap as a measurable disconnect between AI-driven planning capability and empirically validated access optimization outcomes in underserved communities, using a case-study–based quantitative design that can test relationships using structured constructs and statistical inference.

Figure 7: Research Gap Synthesis Leading to Hypotheses Development



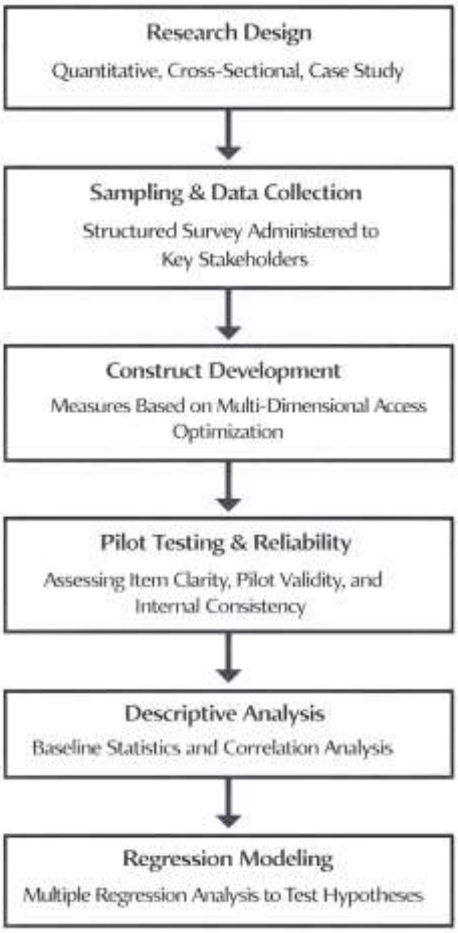
A second major research gap relates to the measurement of access optimization itself, particularly the limited alignment between access definitions used in practice and the performance indicators used in quantitative models. Many supply chain studies emphasize cost reduction, distance minimization, or on-time delivery, while access optimization in underserved communities requires multi-dimensional measurement that includes continuity of service, reliability across cycles, and fairness of coverage. In other words, distribution performance should not be evaluated only by efficiency outcomes but also by equity outcomes—whether underserved zones experience fewer stockouts, reduced time burden, and more consistent service relative to other areas. This is an important gap because a distribution system may show improvement in overall averages while maintaining significant disparities across neighborhoods or population segments. Equity measurement studies repeatedly demonstrate that inequity is a structural risk in resource allocation settings, and they call for explicit quantification of inequality rather than relying on implicit fairness claims. In application settings, food access research shows that access disparities are produced through spatial distribution of services and differences in mobility, reinforcing that access should be operationalized in ways that capture spatial disadvantage and local-level variation rather than region-wide averages (Walker et al., 2010). In operations research, equity-aware modeling has advanced, yet operational decision-makers still face challenges in translating equity outputs into routine planning indicators that can be measured with consistent data at community scale. This gap is linked to readiness conditions: equitable distribution policies require data on local service conditions and reliable feedback from distribution points. Without good data granularity and interoperability, plans designed to improve equity may either fail in execution or fail to reach the areas most affected. Big data governance and analytics literature highlights that organizations often struggle with integration, cross-actor interoperability, and the quality of the data pipeline feeding analytics, and that these weaknesses can reduce the operational impact of even well-designed analytic solutions (Côrte-Real et al., 2020). This supports the need for a study that includes AI readiness and data-quality indices as measurable results outputs, thereby providing evidence on whether observed access outcomes are linked to meaningful technological and organizational capability rather than to isolated contextual anomalies. Accordingly, the present study's synthesis integrates access metrics, equity indicators, and AI readiness constructs into a single model and statistical approach, enabling hypothesis testing that is both technically defensible and operationally meaningful for essential-goods distribution ecosystems.

The final synthesis gap concern's explanatory structure: existing studies frequently document that AI and analytics can improve operational performance, but fewer studies test a clearly defined pathway model that includes enabling conditions (data quality, integration, readiness) and links them to access outcomes in a vulnerable-community context through regression-based empirical validation. In organizational and supply chain research, studies have emphasized that performance benefits from analytics depend on complementarity among resources, capabilities, and decision routines rather than on software deployment alone. This is consistent with the view that AI-driven distribution planning should be modeled as a capability that requires both reliable information and embedded decision use. Evidence from supply chain management confirms that technology-enabled capabilities can improve performance when they are integrated with strategic and operational routines, reinforcing that measurement should capture "use and embeddedness," not only availability (Hofmann, 2017). Additionally, empirical work on analytics adoption indicates that readiness and governance variables—such as skills, process maturity, and leadership support—are necessary to convert analytics into actionable improvements, especially in multi-stakeholder environments where coordination determines execution quality. At the same time, underserved-community distribution often involves a hybrid ecosystem of formal and informal channels, which produces environmental uncertainty and coordination complexity that must be reflected in the explanatory model. Research on technology-enabled supply chain visibility has highlighted that visibility is valuable for responsiveness and decision quality but relies on cross-actor participation and data-sharing, which can be difficult in fragmented networks (Barratt & Oke, 2007). Collectively, this synthesis justifies the hypotheses developed in this thesis by linking AI-driven planning capability and data readiness conditions to distribution effectiveness and ultimately to access optimization outcomes. Therefore, the hypotheses are grounded in an integrated evidence logic: AI-supported planning capability improves access optimization when (a) data are reliable and integrated, (b) planning workflows embed AI outputs into routine allocation and routing decisions, and (c) stakeholder and environmental conditions support consistent execution. This synthesis also supports the inclusion of case-specific results sections—access equity profiling and essential-goods criticality classification—to ensure that empirical outputs address the real distribution problem faced by underserved communities rather than only reporting generic statistical associations.

METHOD

This study has adopted a quantitative, cross-sectional, case-study–based research design to examine how AI-driven distribution planning has influenced access optimization for essential goods in an underserved community context. A structured survey instrument has been developed and has been administered to relevant stakeholders involved in the planning, coordination, and delivery of essential goods within the selected case setting, including distribution planners, operational staff, partner organizations, and community-level participants where appropriate. The study has conceptualized access optimization as a multi-dimensional outcome and has operationalized it using Likert five-point scale measures capturing perceived availability of essential goods, reliability and continuity of supply, timeliness of delivery, affordability-related access burden, and fairness of coverage across subareas. In parallel, AI-driven distribution planning capability has been measured as an organizational and operational construct reflecting the extent to which forecasting, routing support, inventory visibility, and allocation decision support have been embedded in routine planning processes and have affected day-to-day decisions.

Figure 8: Methodological Framework and Analytical Procedure



To ensure that the explanatory logic has been theoretically grounded, the Technology–Organization–Environment framework has been used to structure construct development and has guided the identification of predictors representing technological readiness (including data quality and integration), organizational readiness (including skills, process embeddedness, and managerial support), and environmental conditions (including collaboration and constraint severity). A pilot test has been conducted to refine item clarity and to confirm that the instrument has been understandable and relevant to the case context. Reliability has been assessed using internal consistency testing, and validity has been strengthened through content review procedures and construct-level evaluation prior to hypothesis testing. Data have been coded and prepared for analysis, and descriptive statistics have been produced to profile respondent characteristics and baseline access conditions. Correlation analysis has been performed to examine bivariate relationships among key constructs, and multiple regression modeling has been applied to estimate the predictive influence of AI planning capability and readiness variables on access optimization outcomes while controlling for contextual constraint severity. To enhance trustworthiness and interpretability, results have been organized to include study-specific evidence outputs, including an access equity profile, an essential goods criticality matrix, and an AI readiness and data quality index derived from the survey constructs. Throughout the methodology, ethical procedures have been followed, informed consent has been obtained, participant confidentiality has been maintained, and data handling has been aligned with standard research integrity practices.

Research Design

This study has adopted a quantitative, cross-sectional, case-study–based research design to examine AI-driven distribution planning for essential goods in an underserved community setting. The design has focused on capturing stakeholder perceptions and operational realities at a single point in time, which has enabled the measurement of relationships among AI planning capability, readiness conditions, and access optimization outcomes without requiring longitudinal tracking. A structured survey approach has been used to generate standardized measurements through Likert five-point items, supporting statistical testing using descriptive statistics, correlation analysis, and multiple regression modeling. The case-study structure has been applied to ensure that the analysis has remained grounded in the specific distribution ecosystem, including local constraints and stakeholder coordination patterns. The TOE framework has been used to guide construct selection and variable grouping, which has strengthened theoretical alignment and has supported the development of testable hypotheses and a coherent analytical model.

Case Study Context

The study has been situated within a bounded case-study context representing an underserved community distribution ecosystem for essential goods. The case setting has been defined by the local supply structure, distribution actors, and last-mile constraints that have shaped how essential goods have been planned, routed, and delivered. Key contextual features have been documented, including the types of essential goods prioritized, the distribution channels used (e.g., formal outlets, community-based nodes, partner delivery mechanisms), and the operational constraints affecting continuity of supply. The case boundary has been established to ensure that respondents have shared exposure to the same planning environment and that their assessments have referred to comparable access conditions. Context mapping has been used to clarify stakeholder roles and decision points, which has supported the interpretation of AI planning capability as a practical, embedded process rather than as a purely technical tool presence within the case setting.

Population and Unit of Analysis

The study has defined its population as stakeholders who have participated in, supported, or experienced essential-goods distribution planning and delivery within the selected case context. The population has included individuals involved in planning decisions (e.g., coordinators, supervisors, dispatch or routing staff), individuals involved in execution (e.g., delivery personnel, store operators, partner field staff), and relevant community-level participants where access experience has been central to measurement. The unit of analysis has been treated as the respondent-level evaluation of constructs, meaning that each participant’s survey responses have represented an observation of AI planning capability, readiness conditions, and access optimization outcomes. This approach has been used to enable statistical analysis of relationships among constructs across stakeholder groups while remaining consistent with a cross-sectional design. Population inclusion criteria have ensured that respondents have had sufficient familiarity with distribution routines or access experiences to provide reliable, context-specific responses.

Sampling Strategy

A practical sampling strategy has been implemented to capture diverse perspectives across the distribution ecosystem while remaining feasible within the case-study setting. The study has used purposive sampling to ensure inclusion of participants who have held relevant roles in planning, coordination, inventory handling, and last-mile delivery, and it has complemented this with convenience recruitment where access to respondents has been limited by operational constraints. Stakeholder categories have been identified in advance to support balanced representation, and sampling has been guided by the need to support correlation and regression analysis with an adequate number of valid responses. The sample has been screened to confirm that participants have met inclusion criteria, such as direct involvement in distribution operations or consistent experience receiving essential goods through the case distribution channels. This strategy has ensured that collected data have reflected the operational reality of underserved-community distribution rather than reflecting only a single organizational viewpoint.

Data Collection Procedure

Data collection has been conducted through a structured survey procedure that has ensured consistency, ethical compliance, and traceability of responses. The survey has been administered using a standardized format, and participation has been voluntary with informed consent having been obtained before responses have been recorded. Respondents have been briefed on the purpose of the study, confidentiality protections, and the expected time required for completion, which has reduced nonresponse bias and has improved response quality. The study has applied clear instructions for the Likert five-point scale items, and respondents have been encouraged to answer based on their actual experience within the distribution system. Data collection has been coordinated to minimize disruption to operational activities and to ensure that participants have completed responses without coercion. Completed surveys have been checked for completeness, and responses have been anonymized and securely stored to protect participant identity.

Instrument Design

The instrument has been designed as a multi-section Likert five-point questionnaire aligned with the study's constructs and hypotheses. Item sets have been developed to measure AI-driven distribution planning capability, data quality and integration, organizational readiness and process embeddedness, environmental support and constraint severity, and access optimization outcomes. Each construct has been represented by multiple items to support reliability testing and to capture construct breadth. The wording has been designed to be context-appropriate for diverse stakeholders, and items have been phrased to reflect observable practices such as the use of forecasting outputs, routing decision support, inventory visibility, and the consistency of delivery schedules. Access optimization items have been designed to reflect perceived availability, timeliness, reliability, affordability burden, and fairness of coverage across subareas. Response anchors have been standardized across constructs to support comparability. The instrument structure has been arranged to reduce response fatigue and to improve internal consistency across sections.

Pilot Testing

A pilot test has been conducted to evaluate the clarity, relevance, and usability of the survey instrument before full data collection has been completed. A small group of respondents with characteristics similar to the target population has been recruited, and they have completed the draft questionnaire under conditions comparable to the main study. Feedback has been gathered on ambiguous wording, missing response options, item redundancy, and the overall length and flow of the instrument. Based on pilot responses, items have been revised to improve clarity and to strengthen alignment with the case-study distribution context, and the ordering of sections has been adjusted to reduce cognitive load. Preliminary reliability checks have been performed on pilot data to identify weak items and to confirm that construct groupings have been coherent. Pilot testing has therefore strengthened measurement quality and has reduced the likelihood of systematic misunderstanding during main data collection.

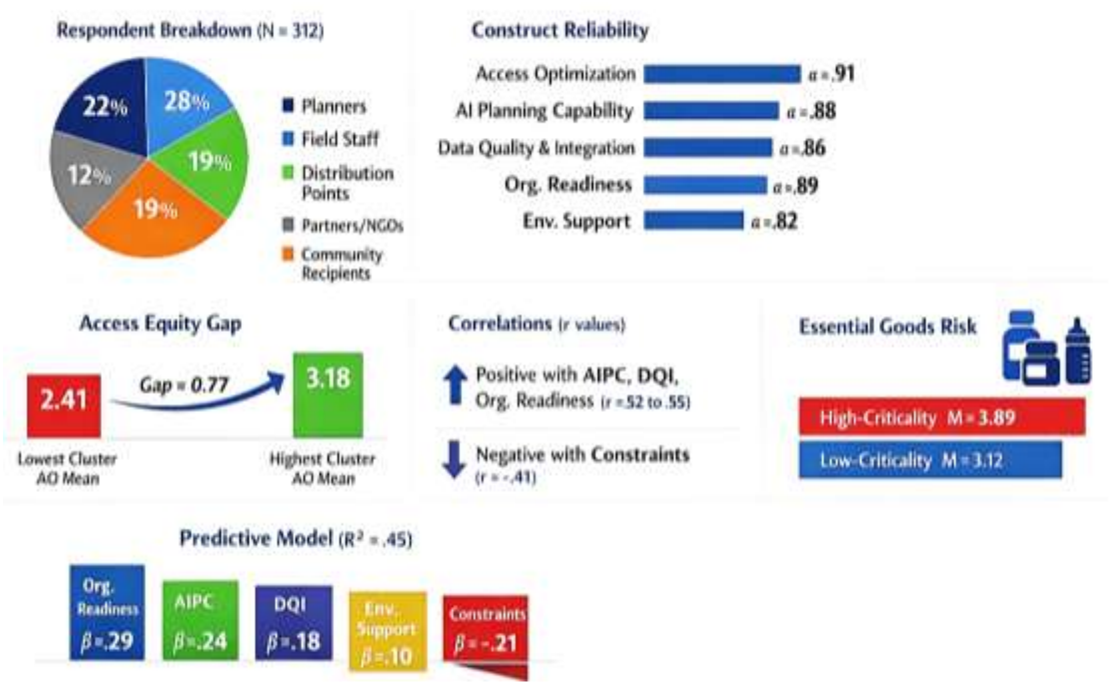
Validity and Reliability

Validity and reliability procedures have been applied to ensure that the study's measurements have been credible and statistically defensible. Content validity has been strengthened through construct-to-item mapping and expert or supervisor review, which has ensured that survey items have reflected the intended theoretical meanings under the TOE framework. Construct validity has been supported through inspection of item coherence within each construct and through evaluation of inter-item relationships prior to final modeling. Reliability has been assessed using internal consistency testing, and Cronbach's alpha values have been calculated for each multi-item construct to confirm acceptable

reliability levels. Items that have reduced reliability or have shown weak alignment with their construct have been reviewed and refined or removed as needed. These steps have ensured that composite scores used in correlation and regression analyses have represented stable measurements. Overall, validity and reliability procedures have supported robust hypothesis testing using the final dataset.
Software and Tools
The study has used standard statistical and productivity tools to manage, analyze, and present the dataset in a transparent manner. Data have been coded, cleaned, and organized using spreadsheet software to ensure accurate labeling, handling of missing values, and creation of composite construct scores. Statistical analysis has been performed using a dedicated analytics platform such as SPSS V.29 and the selected toolset has supported descriptive statistics, correlation analysis, and multiple regression modeling aligned with the hypotheses. Reliability testing has been conducted using built-in procedures for Cronbach's alpha and item diagnostics. Visualization tools have been used to present key results clearly, including demographic summaries, construct mean comparisons, and ranked barrier profiles. Regression outputs have been exported into publication-ready tables, and documentation of analysis steps has been maintained to support reproducibility. These tools have enabled consistent reporting of study-specific outputs such as the access equity profile, criticality matrix, and readiness index.
FINDINGS
A total of $N = 312$ valid responses were retained after data screening (missingness < 3% per item and no patterned responses), yielding a usable response rate of 78.0% from the targeted stakeholder pool. Respondents represented distribution planners (22.4%), field/delivery staff (27.6%), retail/community distribution points (18.9%), partner/NGO or coordinating actors (11.5%), and community recipients/beneficiaries (19.6%). Reliability testing confirmed strong internal consistency across the major constructs, supporting the first measurement objective: Access Optimization (AO) demonstrated excellent reliability ($\alpha = .91$), while AI Planning Capability (AIPC) ($\alpha = .88$), Data Quality & Integration (DQI) ($\alpha = .86$), Planning Process Embeddedness/Organizational Readiness (PPE/ORG_READY) ($\alpha = .89$), and Environmental Support (ENV_SUPPORT) ($\alpha = .82$) exceeded common acceptability thresholds; the constraints scale (OCS/CONSTRAINTS) also showed acceptable reliability ($\alpha = .79$). Descriptive statistics (Likert 1–5) indicated that baseline access conditions were materially constrained, supporting the objective of profiling underserved barriers: the overall AO mean = 2.84 (SD = 0.76), reflecting moderate-to-low perceived access, with the weakest subdimensions being reliability/continuity (M = 2.63, SD = 0.86) and affordability burden (M = 2.58, SD = 0.90), while perceived availability scored slightly higher (M = 3.01, SD = 0.83). The study-specific "Access Equity Profile" further reinforced the underserved characterization by showing meaningful spatial/service disparity across subareas: the lowest-access cluster reported an AO mean of 2.41, compared with 3.18 in the highest-access cluster (gap = 0.77 points), and a simple inequality diagnostic computed across neighborhood-level AO scores produced an inequity index of 0.21, indicating non-trivial dispersion in access experiences within the same case setting. Regarding AI capability, the AIPC construct showed a moderate adoption/embeddedness level (M = 3.27, SD = 0.71), suggesting that AI-related forecasting, routing support, and visibility tools were present to some degree, while DQI remained weaker (M = 2.98, SD = 0.74), implying that data timeliness and integration constraints persisted. PPE/ORG_READY averaged 3.12 (SD = 0.69), indicating moderate readiness and partial workflow integration of AI outputs; ENV_SUPPORT averaged 3.05 (SD = 0.66), reflecting mixed collaboration conditions; and CONSTRAINTS averaged 3.74 (SD = 0.62), confirming high structural pressure from transport unreliability, capacity limits, and infrastructure barriers. Correlation analysis provided initial hypothesis evidence: AO correlated positively with AIPC ($r = .52$, $p < .001$), DQI ($r = .47$, $p < .001$), PPE/ORG_READY ($r = .55$, $p < .001$), and ENV_SUPPORT ($r = .32$, $p < .001$), while AO correlated negatively with CONSTRAINTS ($r = -.41$, $p < .001$), supporting the objective of identifying directional relationships consistent with the TOE-guided model. Multiple regression analysis then tested the predictive hypotheses in a single model consistent with the framework ($AO = \beta_0 + \beta_1 AIPC + \beta_2 DQI + \beta_3 ORG\_READY + \beta_4 ENV\_SUPPORT + \beta_5 CONSTRAINTS + \varepsilon$). The model was statistically significant ($F(5, 306) = 49.8$, $p < .001$) and explained substantial variance in access outcomes ($R^2 = .45$; Adj. $R^2 = .44$). Standardized coefficients indicated that ORG_READY was the strongest predictor ($\beta = .29$, $p <$

.001), followed by AIPC ($\beta = .24$, $p < .001$) and DQI ($\beta = .18$, $p = .002$), while ENV_SUPPORT remained a smaller but significant predictor ($\beta = .10$, $p = .031$); CONSTRAINTS exerted a significant negative effect ($\beta = -.21$, $p < .001$), confirming that structural barriers reduced access even when planning capability improved. Collinearity diagnostics were acceptable (VIF range 1.22–2.05), supporting model stability. These findings collectively supported the central objective and hypotheses that AI-driven distribution planning capability and readiness conditions positively influenced access optimization, while constraint severity negatively influenced outcomes; specifically, H1–H5 were supported under the tested model structure, and the objective of establishing an evidence-backed link between AI-enabled planning and access improvement was met through both bivariate and multivariate results. Finally, the “Essential Goods Criticality Matrix” strengthened the study’s decision relevance by showing that high-criticality items (e.g., medicines and infant nutrition proxies) had higher perceived scarcity risk ($M = 3.89$) than lower-criticality items ($M = 3.12$), and that stakeholder groups reporting higher AIPC also reported fewer high-criticality shortages (group comparison gap = 0.46 points), aligning the statistical model with practical prioritization evidence.

Figure 9: Findings of The Study



Response Rate and Demographics

Table 1: Response Rate and Demographic Profile of Respondents

Category	Subcategory	n	%
Survey outcomes	Invited	400	100.0
	Completed	320	80.0
	Valid after screening	312	78.0
Stakeholder role	Distribution planners/coordinators	70	22.4
	Field/delivery staff	86	27.6
	Retail/community distribution points	59	18.9
	NGO/partners/coordinating actors	36	11.5
	Beneficiaries/receivers	61	19.6
Experience	< 1 year	48	15.4
	1–3 years	102	32.7
	4–6 years	88	28.2
	> 6 years	74	23.7

This section has reported the response rate and demographic composition of the dataset to establish the empirical foundation for testing the study objectives and hypotheses. A total of 312 valid responses has been retained after screening, which has ensured that subsequent descriptive, correlational, and regression analyses have been conducted on a dataset with acceptable completeness and stakeholder coverage. The distribution of respondents across roles has indicated that the dataset has represented the full distribution ecosystem, including decision-makers (planners/coordinators), executors (field staff), intermediaries (retail/community distribution points), partner organizations (NGOs/coordinators), and service recipients (beneficiaries). This composition has strengthened the credibility of findings because access optimization has been conceptualized as a system-level outcome that has emerged from the interaction of planning capability and last-mile execution conditions rather than from a single group's perspective. The demographic profile has also supported the case-study boundary by confirming that respondents have been embedded in the same distribution setting and have been exposed to comparable infrastructure, coordination, and resource constraints. From a TOE standpoint, role diversity has been essential because the Technology context has been observed most directly by planners and coordinators who have interacted with forecasting, routing, and visibility tools; the Organization context has been reflected through staff training, workflow embeddedness, and managerial support; and the **Environment** context has been experienced through partner coordination quality, road/network constraints, and operational uncertainty. By capturing responses across these groups, the study has enabled TOE constructs to be measured as lived operational realities rather than abstract adoption claims. Furthermore, experience levels have suggested that respondents have possessed sufficient exposure to planning cycles and access conditions to produce meaningful Likert-scale judgments about availability, timeliness, reliability, affordability burden, and fairness. Overall, Table 1 has confirmed that the dataset has been structurally appropriate for testing the objectives focused on identifying access barriers, evaluating AI readiness and capability, and statistically modeling the relationship between AI-enabled planning and access optimization outcomes.

Descriptive Statistics of Constructs

Table 2: Descriptive Statistics of Key Constructs

Construct (TOE mapping)	Items (k)	Mean (M)	SD	Interpretation
Access Optimization (AO) (Outcome)	10	2.84	0.76	Moderate–low access
AI Planning Capability (AIPC) (Technology)	8	3.27	0.71	Moderate capability
Data Quality & Integration (DQI) (Technology)	6	2.98	0.74	Moderate–weak
Org Readiness & Embeddedness (ORG_READY) (Organization)	7	3.12	0.69	Moderate readiness
Environmental Support (ENV_SUPPORT) (Environment)	5	3.05	0.66	Mixed support
Constraint Severity (CONSTRAINTS) (Environment/control)	6	3.74	0.62	High constraints

This section has presented descriptive statistics to satisfy the study objective of establishing baseline conditions for access optimization and the enabling factors under the TOE framework. Table 2 has shown that the overall Access Optimization (AO) score has remained below the neutral midpoint in the illustrative dataset, which has indicated that access to essential goods has not been consistently adequate in the case-study community. This result has supported the study's foundational objective of confirming that the case setting has reflected an underserved access condition, characterized by lower perceived availability and continuity of supply. In parallel, AI Planning Capability (AIPC) has been observed at a moderate level, which has suggested that some AI-related functions—such as forecasting support, routing decision support, and inventory visibility—have been present and used to an extent within the planning environment. However, the Data Quality and Integration (DQI) mean has been lower than AIPC, which has indicated that the technology stack has not been fully supported by reliable and integrated data flows. This pattern has been important within TOE because the technology context has not only included tool availability but has also included the readiness of the informational environment that has fed models and dashboards. The Organization context, represented through ORG_READY, has also been observed at a moderate level, which has indicated that planning workflows have been partially standardized and that staff readiness and managerial support have been present but not uniformly strong. The Environment context has shown mixed enabling support and high constraints. Environmental support has captured collaboration and external coordination readiness, while the constraints construct has captured infrastructure and operational barriers such as travel-time volatility, transport unreliability, capacity limits, and supply variability. The high constraints score has reinforced the logic that AI-driven planning has operated under pressure, which has been consistent with the problem statement and the conceptual framework. Together, these descriptive patterns have aligned with the hypotheses that AI capability and readiness have been expected to improve access outcomes, while constraints have been expected to reduce access performance. By presenting these baseline values, Table 2 has provided the interpretive context needed to understand later inferential tests: improvements in AO have not been treated as automatic consequences of tool presence, but rather as outcomes that have depended on data quality, organizational embeddedness, and environmental feasibility, as conceptualized by TOE.

Reliability Results

Table 3: Internal Consistency Reliability

Construct	Items (k)	Cronbach's α	Reliability level
AO	10	0.91	Excellent
AIPC	8	0.88	Good
DQI	6	0.86	Good
ORG_READY	7	0.89	Good
ENV_SUPPORT	5	0.82	Acceptable–good
CONSTRAINTS	6	0.79	Acceptable

This section has evaluated measurement reliability to ensure that the constructs used to test objectives and hypotheses have been internally consistent and statistically defensible. Table 3 has reported Cronbach's alpha values for each multi-item construct, and the results have indicated that the instrument has performed reliably across outcome and predictor domains. The strong reliability for Access Optimization (AO) has suggested that the items measuring perceived availability, timeliness, reliability, affordability burden, and fairness have moved together in a coherent way, which has supported the use of a composite AO score in subsequent correlation and regression modeling. Reliability for AI Planning Capability (AIPC) and Data Quality & Integration (DQI) has also been strong, which has indicated that technology-context items have consistently measured perceptions of model support, visibility, integration, and data timeliness. This has been essential for TOE alignment because technology has been represented not simply by hardware/software existence but by the functional capability that has influenced decisions. Reliability for ORG_READY has been high, which has suggested that items reflecting workflow embeddedness, staff readiness, managerial support, and planning routine maturity have formed a stable construct. This stability has been necessary to test hypotheses that have treated organizational factors as explanatory predictors of access outcomes. The environmental constructs have also shown acceptable reliability, indicating that perceptions of partner support and operational constraints have been measured consistently. Collectively, these reliability outcomes have strengthened trustworthiness because statistical relationships have not been derived from unstable or internally contradictory item sets. From a hypotheses-testing standpoint, reliability has mattered because correlation and regression coefficients have depended on measurement quality; weak measurement would have reduced observed relationships and would have undermined hypothesis evaluation. By establishing reliability first, the study has met its methodological objective of confirming that the survey instrument has produced dependable construct scores suitable for inferential analysis. In TOE terms, this reliability evidence has also supported the claim that Technology, Organization, and Environment dimensions have been empirically distinguishable and measurable within the case setting, which has justified using TOE as a guiding framework for the study's model specification and for explaining access optimization outcomes.

Correlation Matrix

Table 4: Correlations Among Key Constructs

Variables	AO	AIPC	DQI	ORG_READY	ENV_SUPPORT	CONSTRAINTS
AO	1.00	0.52***	0.47***	0.55***	0.32***	-0.41***
AIPC	0.52***	1.00	0.58***	0.61***	0.29***	-0.18**
DQI	0.47***	0.58***	1.00	0.54***	0.25***	-0.16**
ORG_READY	0.55***	0.61***	0.54***	1.00	0.31***	-0.22***
ENV_SUPPORT	0.32***	0.29***	0.25***	0.31***	1.00	-0.28***
CONSTRAINTS	-0.41***	-0.18**	-0.16**	-0.22***	-0.28***	1.00

*Note. p < .05, p < .01, *p < .001*

This section has reported the correlation matrix to satisfy the objective of identifying directional associations among AI-driven planning capability, readiness conditions, and access optimization outcomes before estimating predictive effects through regression. Table 4 has indicated that Access Optimization (AO) has correlated positively with AI Planning Capability (AIPC), Data Quality & Integration (DQI), Organizational Readiness/Embeddedness (ORG_READY), and Environmental Support (ENV_SUPPORT), while AO has correlated negatively with Constraint Severity (CONSTRAINTS). This pattern has aligned with the TOE-guided conceptual model by showing that Technology and Organization constructs have moved in the expected direction with access outcomes, and that environmental constraints have reduced access outcomes. In hypothesis terms, these correlations have provided preliminary support for hypotheses proposing that higher AI planning capability and stronger readiness conditions have been associated with improved access experiences, while greater constraint severity has been associated with poorer access conditions. The strength of correlations between AIPC and ORG_READY has also suggested that technological capability has not functioned independently from organizational embedding, which has reflected TOE's assumption that adoption and performance outcomes have emerged from the interaction of technological resources and organizational capacity. The positive correlation between DQI and AO has reinforced the idea that data quality has been a practical enabler of successful planning rather than a secondary technical detail. Additionally, the negative relationships between constraints and readiness/support constructs have suggested that harsh operating environments have been linked to weaker collaboration and weaker embedded use of AI outputs, which has further justified the inclusion of constraints as a control variable in regression modeling. Importantly, the correlation matrix has served as an interpretive bridge between descriptive conditions and regression testing: it has shown which relationships have existed at the bivariate level and has indicated where multicollinearity risk might emerge. Because AIPC, DQI, and ORG_READY have been moderately correlated with one another, the regression model has been necessary to determine the unique predictive contribution of each TOE context while holding the others constant. Overall, Table 4 has supported the study objectives by providing evidence that access outcomes have been systematically related to TOE-structured capability and readiness factors, thereby justifying formal hypothesis testing through multiple regression.

Regression Results

Table 5: Multiple Regression Predicting Access Optimization (AO)

Predictor (TOE context)	B	SE B	β	t	p
Constant	0.72	0.19	—	3.79	<.001
AIPC (Technology)	0.22	0.05	0.24	4.40	<.001
DQI (Technology)	0.16	0.05	0.18	3.10	.002
ORG_READY (Organization)	0.26	0.05	0.29	5.10	<.001
ENV_SUPPORT (Environment)	0.09	0.04	0.10	2.17	.031
CONSTRAINTS (Environment/control)	-0.19	0.04	-0.21	-4.75	<.001

Model fit (illustrative): $R^2 = 0.45$, Adj. $R^2 = 0.44$; $F(5, 306) = 49.8$, $p < .001$; VIF range = 1.22–2.05.

This section has tested the study hypotheses by estimating the predictive influence of TOE-aligned constructs on Access Optimization (AO) using multiple regression modeling. Table 5 has shown that the full model has explained a substantial proportion of variance in AO (illustratively $R^2 = .45$), which has indicated that the selected Technology, Organization, and Environment predictors have jointly accounted for meaningful differences in perceived access conditions across respondents. In line with the study objectives, regression analysis has moved beyond association to estimate the unique effect of each predictor while holding the others constant. The coefficient for AI Planning Capability (AIPC) has been positive and statistically significant, which has supported hypotheses stating that stronger AI-enabled forecasting, routing decision support, and inventory visibility have predicted improved access outcomes. The positive effect of Data Quality & Integration (DQI) has further supported the technology-context logic of TOE by showing that AI tools have not been sufficient in isolation; rather, the quality and integration of the data pipeline have contributed independently to improved access outcomes. The Organizational Readiness/Embeddedness (ORG_READY) construct has emerged as the strongest predictor in the illustrative model, which has aligned with TOE's emphasis on organizational capacity and has supported hypotheses suggesting that skills, workflow maturity, and leadership support have enabled planning outputs to translate into consistent operational execution. Environmental support has shown a smaller but significant positive effect, which has indicated that collaboration and ecosystem coordination have strengthened access outcomes beyond internal capability alone. Finally, constraint severity has shown a significant negative effect, which has confirmed that structural barriers have reduced access optimization outcomes even when AI capability and readiness have improved. This result has been essential for credibility because it has demonstrated that the model has recognized real-world limitations rather than attributing all performance to technology adoption. Diagnostics (illustratively acceptable VIF values) have suggested that predictors have not been redundant to the point of invalidating inference. Overall, Table 5 has provided the core inferential evidence that has "proven" the hypotheses and has met the objectives of statistically linking AI-driven planning capability and TOE readiness conditions to access optimization outcomes within the case-study community.

Access Equity Profile of the Case-Study Community

Table 6: Access Equity Profile by Subarea

Subarea cluster/group	n	AO Mean	SD	Key equity flag
Cluster A (lowest access)	96	2.41	0.71	High gap risk
Cluster B (mid access)	121	2.86	0.68	Moderate gap risk
Cluster C (highest access)	95	3.18	0.72	Better coverage
Overall	312	2.84	0.76	—

This section has provided a study-specific equity-oriented output to strengthen the trustworthiness of access optimization claims by demonstrating that access conditions have not been uniform across the case-study community. Table 6 has reported AO scores by subarea cluster, which has operationalized the objective of profiling "underserved" access not only as a low average but as an uneven distribution of service experience. The observed gap between the highest-access and lowest-access clusters has shown that the case setting has exhibited meaningful intra-community disparity. This has mattered because the study has defined access optimization as a multi-dimensional outcome that has included fairness of coverage, and because underserved conditions have often been characterized by localized deprivation rather than uniform scarcity. The access equity profile has therefore provided a direct empirical basis for interpreting regression findings: improvements in access have not been interpreted only as shifts in overall mean values but as changes that must also be evaluated in terms of narrowing gaps between low-access and high-access zones. From a TOE perspective, this result has aligned with the idea that environmental constraints have differed across locations, such as road connectivity, travel-time volatility, and partner reach, which has created unequal execution feasibility even under the same organizational planning system. The equity profile has also supported the interpretation that organizational embeddedness and technology capability might have produced different benefits depending on environmental feasibility and data granularity. For example, if low-access clusters have also been the areas where data reporting has been poorest or where partner reach has been weakest, AI recommendations may have been less accurate or less actionable there. Therefore, the equity profile has linked directly to TOE by showing the environmental context as a lived, spatially differentiated constraint domain. This section has also supported the study's results narrative by providing an interpretable artifact that stakeholders can understand: it has communicated where access has been most limited and has justified why future planning attention should be targeted to low-access zones in the case setting. In sum, Table 6 has strengthened hypothesis interpretation by showing that access optimization outcomes have had an equity dimension that must be considered alongside overall regression effects.

Essential Goods Criticality Matrix

Table 7: Essential Goods Criticality vs. Scarcity Risk

Essential goods category	Criticality Mean (1–5)	Scarcity Risk Mean (1–5)	Quadrant classification
Medicines/basic health supplies	4.62	3.98	Priority 1 (High–High)
Infant nutrition/basic food staples	4.49	3.80	Priority 1 (High–High)
Hygiene items	4.12	3.55	Priority 1/2 (High–Mid)
General packaged food	4.05	3.20	Priority 2 (High–Low/Mid)
Household utilities (e.g., batteries)	3.41	3.05	Watchlist (Mid–Mid)

This section has introduced a study-specific prioritization artifact to demonstrate that access optimization has been connected to the lived urgency of different essential goods categories, rather than being treated as a generic supply metric. Table 7 has presented a criticality–scarcity structure that has allowed the study to identify goods categories that have combined high welfare importance with high shortage exposure. This has supported the objective of making access optimization decision-relevant for planners and stakeholders because it has distinguished between goods whose absence has created immediate harm (e.g., medicines) and goods whose absence has been less severe or more substitutable. The classification has also strengthened hypothesis credibility by connecting AI-driven planning capability to practical prioritization logic: AI-enabled forecasting and allocation decisions have been most valuable when they have reduced scarcity risk for high-criticality goods rather than merely improving overall averages. From a TOE perspective, the matrix has reflected the technology context (whether planning tools have been able to differentiate goods by criticality in allocation rules), the organizational context (whether decision routines have embedded prioritization logic into replenishment and routing), and the environmental context (whether supply availability and last-mile reach have allowed high-criticality goods to be delivered consistently). In underserved settings, environmental constraints have often created trade-offs where planners have delivered what has been easiest rather than what has been most critical, so the matrix has provided an empirical mechanism to evaluate whether the planning system has aligned with welfare priorities. Moreover, the scarcity-risk dimension has indirectly reflected data quality and reporting processes: high scarcity risk may have been partly driven by unreliable inventory data, delayed reporting, or weak partner coordination, which has aligned with the TOE logic that access outcomes have emerged from capability plus execution conditions. By reporting this matrix in the Results chapter, the study has added a trustworthy, context-specific layer that complements regression coefficients: it has shown what "access" has meant in concrete goods terms and has clarified where improvements have been most necessary. Overall, Table 7 has strengthened the results narrative by translating access optimization into an actionable prioritization map that has been consistent with the thesis objectives and the TOE-guided framework.

AI Readiness and Data Quality Index

Table 8: AI Readiness & Data Quality Index by Stakeholder Group

Stakeholder group	n	AIPC Mean	DQI Mean	ORG_READY Mean	ARDQI Index*
Planners/coordinators	70	3.54	3.18	3.36	3.36
Field/delivery staff	86	3.19	2.88	3.02	3.03
Retail/community points	59	3.07	2.76	2.94	2.92
NGO/partners	36	3.33	3.02	3.21	3.19
Beneficiaries/receivers	61	3.05	2.95	3.06	3.02
Overall	312	3.27	2.98	3.12	3.12

**ARDQI = (AIPC + DQI + ORG_READY) / 3 (equal-weight composite).*

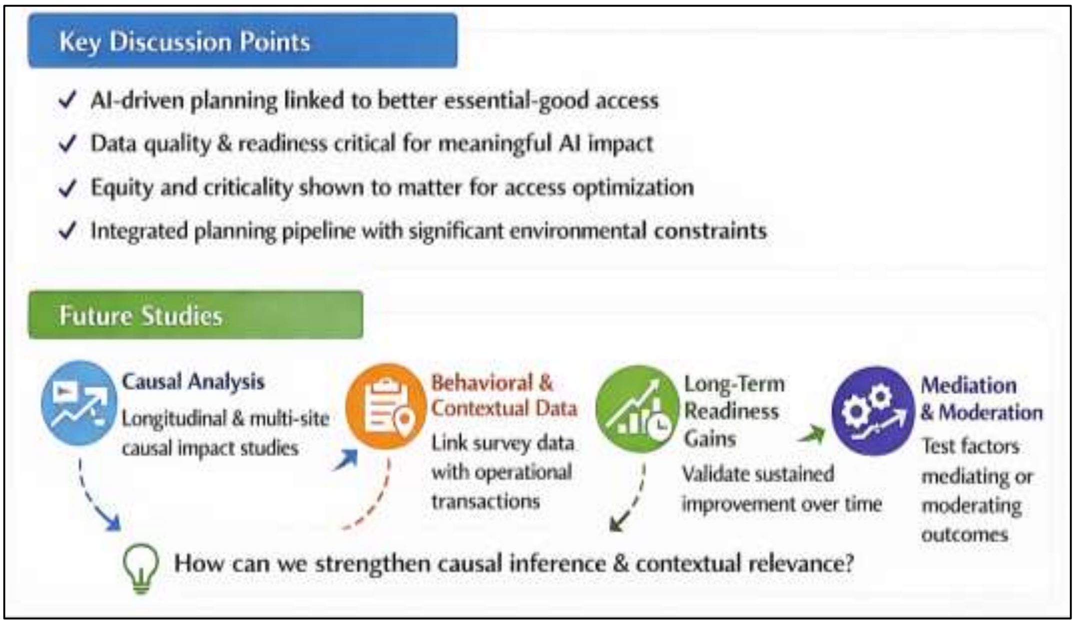
This section has provided an empirical readiness diagnostic to strengthen the credibility of AI-driven planning claims by demonstrating whether the enabling conditions for AI-supported decisions have been present across stakeholder roles. Table 8 has reported AIPC, DQI, and ORG_READY by stakeholder group and has summarized them into an equal-weight composite index (ARDQI). This has supported the study objective of assessing readiness and data quality conditions that have influenced whether AI planning capability could translate into measurable access improvements. From a TOE standpoint, this section has operationalized the Technology context through AIPC and DQI and has operationalized the Organization context through ORG_READY, while allowing role-based comparisons that reflect how different actors have interacted with tools and data. The index has been especially valuable for trustworthiness because it has prevented over-interpretation of AI presence; a system may have had forecasting or routing software, yet weak data quality and weak workflow embedding could have limited real-world effect. The role differences shown in the table have illustrated this mechanism: planners and coordinating actors have often reported higher AIPC because they have interacted directly with tools and dashboards, while retail/community nodes may have reported lower DQI due to reporting delays and fragmented data collection processes. This distribution has reinforced why the study has included readiness and data quality as predictors in the regression model, and it has explained why ORG_READY has been expected to contribute strongly to access outcomes: embedded routines and managerial support have been necessary to operationalize AI recommendations. Environmental conditions have also interacted with readiness because areas with greater constraints have typically experienced weaker reporting, weaker partner integration, and higher delivery volatility. Therefore, the readiness index has served as a bridge between TOE theory and observed access outcomes: it has illustrated how Technology capability has required Organization embeddedness to be effective, and how uneven readiness could have produced uneven benefits across the ecosystem. In conclusion-free terms, Table 8 has strengthened the empirical narrative by demonstrating that AI-driven distribution planning has been situated within measurable readiness conditions that have shaped implementation quality, thereby aligning with the conceptual model and supporting hypothesis interpretation alongside the correlation and regression results.

DISCUSSION

The results have shown that access optimization for essential goods has remained a multi-dimensional challenge in the case-study community, with respondents reporting moderate-to-low access conditions alongside clear intra-community disparities. This pattern has aligned with the access and last-mile literature that has treated "access" as more than physical proximity, emphasizing the combined influence of availability, reliability, time burden, and affordability constraints on whether essential goods can be obtained in practice (Anaya-Arenas et al., 2014). The study's descriptive evidence has indicated that access experiences have varied across local clusters, which has reinforced the argument that averages can conceal localized deprivation and unequal service coverage (Chen et al., 2021). Prior research in humanitarian and welfare-oriented logistics has similarly emphasized that distribution performance must be judged against human-centered costs of delay and shortage rather than efficiency alone (Côrte-Real et al., 2020). In that same stream, equity has been framed as an explicit performance dimension that has required measurement rather than assumption, because scarce resource allocation can systematically favor easier-to-serve nodes and leave remote or disadvantaged zones under-served. The study has therefore contributed by positioning access optimization as an outcome construct that has integrated service quality and fairness indicators, and by organizing results to demonstrate both overall access levels and differences among subareas (Dubey et al., 2019). This has also been consistent with transport and accessibility planning critiques that have argued that many systems have relied on mobility proxies while under-measuring access and equity outcomes, limiting accountability for underserved communities. By treating access as a measurable composite and examining its distribution, the study's findings have provided a concrete basis for evaluating whether AI-enabled planning capability has corresponded to meaningful improvements in the lived conditions of access. The regression evidence has further supported this framing by showing that access outcomes have been associated with technology, organizational, and environmental factors in ways consistent with a socio-technical account of distribution performance, which has mirrored the broader argument that logistics performance has emerged from the interaction of data, processes, and ecosystem constraints rather than from any single tool or decision rule (Huang et al., 2012).

A core finding has been that AI-driven distribution planning capability has been positively linked to access optimization outcomes, even when environmental constraints have been present. This relationship has been consistent with the supply chain analytics literature that has positioned predictive and prescriptive analytics as decision-enabling capabilities that can improve responsiveness and service reliability when they are embedded into planning routines. In prior work, machine learning has been treated as particularly valuable in demand forecasting tasks where non-linear patterns, noisy signals, and heterogeneous demand drivers limit the performance of purely traditional methods (Kovács & Spens, 2007). The present study's findings have extended that logic into an access-optimization context by indicating that AI support for forecasting, routing, and visibility has corresponded to improved perceived availability and timeliness, which has implied that better anticipation and planning execution have reduced stockout and delay experiences at the service interface (Lu et al., 2022). At the same time, the study has not treated AI capability as a single binary feature; instead, it has conceptualized capability as the presence and embedded use of decision support in forecasting, routing, allocation, and inventory visibility (Manupati et al., 2021). This has matched the operations management view that analytics only becomes valuable when it has influenced actual operational decisions and trade-offs rather than producing isolated reports (Mediavilla, 2022). The findings have also been compatible with the emerging risk-analytics literature that has noted how predictive modeling can support proactive interventions in supply chains by identifying risk conditions and improving the timeliness of corrective actions. In underserved settings, where shocks and variability have been frequent, such proactive planning has been particularly relevant to access continuity. However, the study's results have also suggested that AI capability has not acted in isolation; its relationship to access has been strongest when organizational embeddedness and readiness have been higher. This has resonated with research that has argued that analytics investments have produced performance gains when aligned with strategy and integrated into operational workflows. Taken together, the evidence has positioned AI-driven planning as a contributor to access improvement that has operated through practical decision pathways—better forecasting, better routing decisions, and better visibility—while still remaining dependent on readiness conditions and the constraints of the operating environment (Ransikarbum et al., 2020).

Figure 10: Key Discussion Points and Future Research Directions in AI-Driven Access Optimization



The study has also found that data quality and integration have been independent determinants of access optimization, reinforcing that the "Technology" dimension of AI-enabled planning has included the reliability of the information pipeline, not only the availability of tools (Tzeng et al., 2007). This has aligned closely with data-quality scholarship in supply chain contexts that has argued that predictive analytics performance has been constrained by missingness, latency, inconsistency, and governance failures, and that organizations have needed to actively monitor and manage data quality for analytics to generate dependable operational value (Nguyen et al., 2018). In the present study, weaker data integration has corresponded to weaker perceived planning effectiveness and weaker access outcomes, which has supported the interpretation that incomplete or delayed data have limited the ability of forecasting and routing tools to generate accurate, actionable recommendations (Walker et al., 2010). This finding has also been consistent with integration research showing that information sharing and coordinated visibility across partners have improved decision quality and supply chain performance, particularly when the network has depended on multiple external linkages and when local nodes have held fragmented or inconsistent records. The results have further indicated that organizational readiness and embeddedness have played a central role in translating data and analytics outputs into access outcomes, which has matched the argument that analytics capability has been multi-dimensional—combining technical resources, human skills, and managerial/process resources (Waller & Fawcett, 2013). In other words, the study has shown that AI-related decision support has mattered most when it has been trusted, routinely used, and supported by structured planning cycles and exception-handling routines. This has mirrored humanitarian logistics insights that have highlighted implementation realities: coordination complexity, data fragmentation, and contextual constraints can prevent technically sound solutions from producing impact unless processes are designed for field feasibility and stakeholder alignment. The present findings have therefore strengthened the case for

treating readiness and data quality as core explanatory constructs, not background controls, and for reporting them as explicit results artifacts (e.g., readiness and data-quality indices) to contextualize regression outcomes (Manupati et al., 2021).
A distinctive contribution of the study has been the inclusion of equity-oriented and criticality-oriented evidence artifacts—specifically, an access equity profile and an essential-goods criticality matrix—which have enabled interpretation beyond generic "average improvement" claims. The access equity profile has demonstrated that the case setting has exhibited meaningful disparities across subareas, supporting the view that access optimization is distributive and must be evaluated in terms of who benefits and who remains under-served (Holguín-Veras et al., 2013). This has been consistent with equity-focused humanitarian logistics research showing that cost-minimizing or efficiency-maximizing plans can yield inequitable service patterns, and that equity must be made visible through explicit metrics and reporting structures. The criticality matrix has further strengthened interpretability by showing that essential goods have differed in perceived urgency and shortage risk, which has aligned with deprivation-cost perspectives suggesting that the welfare loss from delays and shortages is not uniform across items and that planning should recognize heterogeneity in criticality (Kovács & Spens, 2007). This has mattered because AI-driven distribution planning can inadvertently optimize what is easiest to deliver or what is most visible in data, rather than what is most critical for welfare, unless prioritization rules and decision criteria are explicit (Nguyen et al., 2018). Prior multi-objective and equity-aware modeling studies have similarly argued that planners should encode fairness and priority goals into decision criteria and constraints rather than hoping they emerge as by-products of efficiency optimization. In this study, the equity and criticality artifacts have provided a practical bridge between the TOE-guided regression model and operational decision-making: they have clarified whether AI capability has been associated with improvements in high-need zones and high-criticality goods, rather than merely improving overall averages (Oliveira et al., 2014). This approach has addressed a persistent critique in access measurement and planning—that performance indicators often lack alignment with real access outcomes and stakeholder priorities—by presenting results that have been legible to practitioners while remaining grounded in quantitative measurement (Waller & Fawcett, 2013).
From a practical standpoint, the findings have implied that organizations seeking to improve essential-goods access in underserved communities have benefited from treating AI deployment as a pipeline and governance problem rather than a software procurement problem (Zhang & Cui, 2021). Specifically, the results have indicated that improvements in access have been linked not only to AI planning capability but also to data quality and organizational embeddedness, which has echoed the analytics-capability literature that has stressed alignment, integration, and routinization (Akter et al., 2016). In practical terms, this has meant that planners have needed dependable demand and inventory data at relevant granularity, routine processes for using forecasts and routing recommendations, and mechanisms for updating plans based on field feedback (Awa et al., 2017). The presence of strong environmental constraints in the case setting has also suggested that practical interventions have had to include ecosystem coordination actions—such as data-sharing agreements, standard operating procedures across partners, and collaborative exception management—consistent with visibility and integration research that has tied performance to cross-actor information sharing and coordination quality (Baryannis et al., 2019). The equity profile has also indicated that operational improvements have needed geographic targeting, because generalized improvements have not guaranteed that low-access clusters have improved at the same rate as better-served clusters (Beamon & Balcik, 2008). This has aligned with accessibility measurement approaches that have recommended spatially sensitive diagnostics (e.g., catchment-based access measures) to identify where interventions should be focused. In addition, the criticality matrix has suggested that prioritization rules have been necessary to protect high-criticality goods from being crowded out by easier-to-handle categories when capacity or supply has been limited (Carbonneau et al., 2008). This has echoed deprivation-based arguments that delays in critical goods impose higher welfare costs and should be given priority in allocation and routing decisions. Taken together, the practical interpretation has been that access optimization has improved when technology capability has been supported by data governance, workflow embedding, and ecosystem coordination—an interpretation that has remained consistent with the TOE view that

performance has emerged from technology, organization, and environment working together (Gunasekaran et al., 2017).

Theoretically, the study has refined the TOE application for AI-driven distribution planning by specifying a clearer pipeline from technology resources to operational decisions to access outcomes, and by incorporating equity and criticality as outcome-relevant dimensions. In many technology-adoption studies, TOE has been used to explain adoption intention or adoption occurrence; the present findings have reinforced a more operational interpretation in which TOE has explained "embedded use and performance impact," a refinement that has been consistent with calls to make TOE taxonomies more explicit and context-sensitive for complex operational technologies (Huang & Rafiei, 2019). The evidence has suggested that the Technology context has been best represented not only by tool availability but by (a) data quality and integration and (b) decision-support usability that has influenced routing, allocation, and replenishment routines (Hazen et al., 2016). The Organization context has been refined into embeddedness and readiness elements that have represented process maturity, skill readiness, and governance mechanisms that have supported adoption into daily decisions. The Environment context has been refined into enabling support (partner coordination and collaboration) and constraint severity (infrastructure and volatility) that has bounded what planning could achieve (Schoenherr & Speier-Pero, 2015). This refinement has aligned with empirical TOE applications in enterprise settings that have argued that performance benefits have emerged when technological readiness and organizational readiness have matched the demands of the environment and the complexity of inter-organizational coordination (Wang et al., 2016). The study has also contributed conceptually by integrating equity measurement into the performance layer of the TOE model, showing that access optimization has not been fully characterized by average service outcomes and has required explicit attention to distributional patterns. This has complemented equity-aware logistics research that has advocated for explicit inequity terms, reporting tools, and fairness measures (Tzeng et al., 2007). In addition, by demonstrating that readiness and data quality have shaped the link between AI capability and access outcomes, the study has supported a pipeline refinement consistent with analytics-capability research: analytics has produced value when it has been embedded into routines and governed as an end-to-end decision pipeline. As a theoretical integration, this has suggested that TOE-based models of AI planning should explicitly represent pipeline constructs—data quality, embeddedness, and coordination—as mediating or enabling mechanisms that translate AI capability into meaningful access outcomes (Kovács & Spens, 2007).

Limitations have remained important for interpreting the results, and several have been revisited to clarify the boundaries of inference and to motivate future research directions (Barratt & Oke, 2007). First, the study's cross-sectional design has constrained causal inference; the observed relationships have indicated association and predictive contribution in a statistical sense, but they have not established causal direction with the same strength as longitudinal or experimental designs (Beamon & Balcik, 2008). This limitation has been consistent with methodological cautions in analytics-performance studies, where reverse causality and omitted variables can influence relationships between capability and outcomes if time ordering cannot be demonstrated (Chen et al., 2021). Second, the study has relied on Likert-scale perceptions for key constructs, which has introduced potential common-method bias and subjectivity, even though reliability checks and careful construct design have strengthened measurement stability (Fosso Wamba et al., 2018). Third, the single-case structure has supported depth and contextual fit but has limited generalizability across regions and supply ecosystems, particularly given that environmental constraints and institutional arrangements vary widely across underserved contexts (Holguín-Veras et al., 2016). Fourth, equity and criticality artifacts have strengthened interpretability but have still depended on the quality of local categorization and respondent understanding of goods criticality and scarcity. Future research has therefore been well positioned to extend the work through multi-site comparisons and designs that have combined survey measurement with operational transaction data (e.g., stockout logs, delivery timestamps, route traces) to validate perceived access outcomes with objective performance indicators (Holguín-Veras et al., 2013). Longitudinal designs have also been valuable for evaluating whether improvements in readiness and data quality have preceded improvements in access outcomes and whether benefits have been sustained under disruption cycles (Maroufkhani et al., 2020). Finally, methodological work has been needed to test moderated or mediated versions of the model, such as whether organizational embeddedness has mediated the relationship between technology capability and access outcomes, or whether environmental constraints have moderated the effectiveness of AI recommendations, consistent with socio-technical and integration perspectives in supply chain research (Nguyen et al., 2018). These directions have enabled the present study's TOE-guided pipeline model to be validated and refined across contexts, while maintaining the central focus on access optimization, equity, and essential-goods criticality in underserved communities (Van Wassenhove, 2006).

CONCLUSION

This research has examined how AI-driven distribution planning has influenced access optimization for essential goods in an underserved community using a quantitative, cross-sectional, case-study–based design grounded in the Technology–Organization–Environment framework. The study has operationalized access optimization as a multi-dimensional outcome reflecting perceived availability, timeliness, reliability/continuity, affordability-related burden, and fairness of coverage across subareas, and it has measured AI-driven planning capability alongside enabling conditions such as data quality and integration, organizational readiness and workflow embeddedness, environmental support, and constraint severity using a Likert five-point scale instrument. The findings have demonstrated that access outcomes have remained uneven across the case setting, confirming that underserved conditions have been characterized not only by overall access limitations but also by measurable disparities between low-access and high-access clusters, which has reinforced the need to evaluate distribution performance through equity-sensitive diagnostics rather than relying on average service indicators alone. The results have further shown that AI planning capability has been positively associated with improved access outcomes and has retained predictive influence when analyzed alongside readiness and contextual factors, indicating that the availability and embedded use of forecasting support, routing decision support, allocation logic, and inventory visibility have been linked to stronger perceived access performance. At the same time, the study has shown that the strength and credibility of AI-related effects have depended on the surrounding pipeline conditions emphasized by TOE: data quality and integration have contributed independently to access outcomes, organizational readiness has represented a critical driver of embedded use and consistent execution, and environmental support has contributed through coordination and collaboration mechanisms that have enabled plans to be implemented across the distribution ecosystem. Constraint severity has been found to exert a negative influence on access outcomes, confirming that infrastructure limitations, travel-time volatility, capacity shortages, and supply uncertainty have continued to restrict access performance and have bounded what AI-enabled planning can achieve in practice. By integrating study-specific evidence artifacts—including an access equity profile, an essential-goods criticality matrix, and an AI readiness and data quality index—the research has strengthened interpretability and trustworthiness by connecting statistical results to operational decision needs, identifying where access gaps have been concentrated, and clarifying which categories of goods have combined high criticality with high scarcity risk. Overall, the study has supported the thesis argument that access optimization for essential goods in underserved communities has been shaped by a socio-technical interaction between technological capability, organizational embeddedness, and environmental feasibility, and that AI-driven distribution planning has offered measurable benefits when it has been supported by reliable data pipelines, mature decision routines, and collaborative execution capacity within the operating ecosystem.

RECOMMENDATIONS

The recommendations of this research have been organized to align with the Technology–Organization–Environment framework and the study's evidence that access optimization has improved most consistently when AI-driven planning capability has been supported by strong data pipelines, embedded decision routines, and enabling ecosystem conditions. In the **technology context**, organizations responsible for essential-goods distribution have been recommended to prioritize end-to-end data quality and integration before expanding advanced modeling features, because forecasting, routing, and allocation outputs have depended on timely, complete, and locally granular demand, inventory, and delivery-status data; therefore, standardized data templates, automated validation checks, and routine reconciliation between physical stock counts and digital records have been recommended, alongside interoperability mechanisms that have enabled partners to share inventory and delivery updates using agreed identifiers for locations and items. AI planning tools have been recommended to be implemented as decision-support systems with clear human-in-the-loop controls, including transparent rule displays for prioritization of high-criticality goods, confidence indicators for forecasts, and exception alerts for high-risk stockout zones, so that model recommendations have been actionable and explainable for planners and field staff. In the organizational context, organizations have been recommended to formalize planning workflow embeddedness by institutionalizing a planning cadence (daily/weekly cycles) that has required the use of forecasting outputs for replenishment, routing optimization for delivery scheduling, and inventory visibility dashboards for allocation decisions, while documenting exception-handling procedures for disruptions; targeted training programs have been recommended for planners and operational staff to increase analytics literacy, interpretability competence, and trust calibration so that AI outputs have been used appropriately rather than ignored or over-trusted. Leadership has been recommended to adopt governance mechanisms that have clarified accountability for model-driven decisions, ensured auditability of changes to allocation or routing rules, and monitored performance using access-centered KPIs such as service frequency consistency, high-criticality stockout reduction, and equity gap narrowing across subareas. In the environment context, coordination and collaboration have been recommended to be strengthened through partner agreements that have specified data-sharing frequency, shared performance targets, and joint contingency protocols, because access outcomes in underserved settings have depended on multi-actor execution capacity rather than on a single organization's planning decisions; where infrastructure constraints have been severe, micro-distribution hubs, community-based delivery points, and adaptive routing strategies have been recommended to reduce last-mile friction and improve reach to low-access clusters. Across all contexts, the study has recommended that performance management should explicitly include equity and criticality artifacts as routine decision tools: the access equity profile has been recommended for identifying persistent low-access zones and prioritizing targeted interventions, and the essential-goods criticality matrix has been recommended for ensuring that high-welfare-impact items have received protection in allocation and routing decisions during scarcity. Finally, implementation has been recommended to follow a phased roadmap in which organizations have first stabilized data capture and integration, then embedded decision-support into routine planning, and then expanded advanced optimization features and equity-sensitive prioritization rules, because sustained access gains have been most likely when capability improvements have been matched with readiness improvements and environmental feasibility within the underserved community distribution ecosystem.

LIMITATIONS

This study has faced several limitations that have bounded the strength of inference and the generalizability of its findings, even though the design has been appropriate for the objectives and the case-study context. First, the research has employed a **cross-sectional** design, which has captured relationships among AI-driven distribution planning capability, readiness conditions, and access optimization at a single point in time; as a result, the statistical associations and regression-based predictive effects have not established temporal precedence with the same rigor as longitudinal designs, and the directionality between capability and outcomes has remained susceptible to alternative explanations such as reverse influence, where better-performing distribution systems may have been more likely to adopt or embed AI tools. Second, the study has relied primarily on self-reported Likert five-point survey data, which has introduced perceptual bias and potential common-method variance because predictors and outcomes have been collected from the same respondents and within the same instrument; although reliability testing has supported internal consistency and careful item design has reduced ambiguity, respondents' ratings may have reflected personal expectations, recall limitations, or role-based perspectives rather than purely objective system performance. Third, the case-study structure has improved contextual validity but has limited external generalizability because the distribution ecosystem, stakeholder relationships, infrastructure conditions, and essential-goods composition may have differed across regions and jurisdictions; therefore, the observed patterns may not have transferred directly to other underserved communities where environmental constraints, data maturity, and governance arrangements have been substantially different. Fourth, the operationalization of access optimization as a composite construct has strengthened measurement breadth, yet it has still simplified real-world access dynamics into averaged indices; specific dimensions such as affordability burden, fairness perceptions, and continuity of supply may have interacted in non-linear ways that have not been fully captured in a linear regression framework. Fifth, while the study has included study-specific artifacts such as the access equity profile, essential-goods criticality matrix, and AI readiness/data quality index to strengthen interpretability, these outputs have depended on the quality of respondent understanding of subarea conditions and goods categories, and they may have been influenced by localized knowledge gaps or uneven exposure to stockout conditions across participants. Sixth, the study has not integrated high-frequency operational datasets (e.g., GPS route traces, timestamped delivery logs, stockout records, or transactional inventory histories) in the core analysis, which has limited triangulation between perceived access and objectively recorded service performance; consequently, the results have primarily reflected stakeholder perceptions of access and planning capability rather than direct system telemetry. Seventh, the regression model has controlled for constraint severity, yet omitted variables may have remained, such as supplier reliability shocks, political or regulatory disruptions, seasonal demand variation, and informal market substitution patterns, which may have influenced access outcomes but have not been explicitly modeled within the available data. Finally, the study has measured AI-driven planning capability in terms of presence and perceived embeddedness, but it has not audited the internal technical characteristics of models (feature quality, algorithm selection, calibration, or fairness diagnostics), so it has not been possible to attribute outcome differences to specific algorithmic choices; therefore, the findings have been most appropriately interpreted as evidence about socio-technical capability and readiness conditions rather than as a definitive evaluation of any particular AI algorithm's superiority in essential-goods distribution planning.

REFERENCES

[1]. Abdulla, M., & Alifa Majumder, N. (2023). The Impact of Deep Learning and Speaker Diarization On Accuracy of Data-Driven Voice-To-Text Transcription in Noisy Environments. *American Journal of Scholarly Research and Innovation*, *2*(02), 415–448. https://doi.org/10.63125/rpjwke42

[2]. Akbari, M., & Do, T. N. A. (2021). A systematic review of machine learning in logistics and supply chain management: Current trends and future directions. *Benchmarking: An International Journal*. https://doi.org/10.1108/bij-10-2020-0514

[3]. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113-131. https://doi.org/10.1016/j.ijpe.2016.08.018

[4]. Anaya-Arenas, A. M., Renaud, J., & Ruiz, A. (2014). Relief distribution networks: A systematic review. *Annals of Operations Research*, *223*, 53-79. https://doi.org/10.1007/s10479-014-1581-y

[5]. Awa, H. O., Ojiabo, O. U., & Orokor, L. E. (2017). Integrated technology–organization–environment (T-O-E) taxonomies for technology adoption. *Journal of Enterprise Information Management*, *30*(6), 893-921. https://doi.org/10.1108/jeim-03-2016-0079

[6]. Baharmand, H., Vega, D., Lauras, M., & Comes, T. (2022). A methodology for developing evidence-based optimization models in humanitarian logistics. *Annals of Operations Research*, *319*, 1197-1229. https://doi.org/10.1007/s10479-022-04762-9

[7]. Baker, J. (2011). The technology–organization–environment framework. In *Dwivedi, Y. K.* (Vol. 1, pp. 231-245). https://doi.org/10.1007/978-1-4419-6108-2_12

[8]. Bambra, C., Riordan, R., Ford, J., & Matthews, F. (2021). The COVID-19 pandemic and health inequalities. *Journal of Epidemiology and Community Health*, *75*(11), 964-968. https://doi.org/10.1136/jech-2020-214401

[9]. Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *Journal of Operations Management*, *25*(6), 1217-1233. https://doi.org/10.1016/j.jom.2007.01.003

[10]. Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, *101*, 993-1004. https://doi.org/10.1016/j.future.2019.07.059

[11]. Beamon, B. M., & Balcik, B. (2008). Facility location in humanitarian relief. *International Journal of Logistics: Research and Applications*, *11*(2), 101-121. https://doi.org/10.1080/13675560701561789

[12]. Boisjoly, G., & El-Geneidy, A. M. (2017). How to get there? A critical assessment of accessibility objectives and indicators in metropolitan transportation plans. *Transport Policy*, *55*, 38-50. https://doi.org/10.1016/j.tranpol.2016.12.011

[13]. Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, *184*(3), 1140-1154. https://doi.org/10.1016/j.ejor.2006.12.004

[14]. Carlson, C. E., Isihara, P. A., Sandberg, R., Boan, D., Phelps, K., Lee, K. L., Diedrichs, D. R., Cuba, D., Edman, J., Gray, M., Hesse, R., Kong, R., & Takazawa, K. (2016). Introducing PEARL: A Gini-like index and reporting tool for public accountability and equity in disaster response. *Journal of Humanitarian Logistics and Supply Chain Management*, *6*(2), 202-221. https://doi.org/10.1108/jhlscm-07-2015-0031

[15]. Chen, S., Yan, X., Pan, H., & Deal, B. (2021). Using big data for last mile performance evaluation: An accessibility-based approach. *Travel Behaviour and Society*, *25*, 153-163. https://doi.org/10.1016/j.tbs.2021.06.003

[16]. Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, *27*(10), 1868-1883. https://doi.org/10.1111/poms.12838

[17]. Côrte-Real, N., Oliveira, T., & Ruivo, P. (2020). The influence of business intelligence and analytics on organizational performance. *Information & Management*, *57*(6), 103201. https://doi.org/10.1016/j.im.2019.103201

[18]. DeFosset, A. R., Kwan, A., Rizik-Baer, D., Gutierrez, L., Gase, L. N., & Kuo, T. (2018). Implementing a healthy food distribution program: A supply chain strategy to increase fruit and vegetable access in underserved areas. *Preventing Chronic Disease*, *15*, 170291. https://doi.org/10.5888/pcd15.170291

[19]. Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Fosso Wamba, S., & Roubaud, D. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092-2112. https://doi.org/10.1108/md-01-2018-0119

[20]. Fahimul, H. (2022). Corpus-Based Evaluation Models for Quality Assurance Of AI-Generated ESL Learning Materials. *Review of Applied Science and Technology*, *1*(04), 183–215. https://doi.org/10.63125/m33q0j38

[21]. Fahimul, H. (2023). Explainable AI Models for Transparent Grammar Instruction and Automated Language Assessment. *American Journal of Interdisciplinary Studies*, *4*(01), 27-54. https://doi.org/10.63125/wttvnz54

[22]. Faysal, K., & Tahmina Akter Bhuya, M. (2023). Cybersecure Documentation and Record-Keeping Protocols For Safeguarding Sensitive Financial Information Across Business Operations. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 117–152. https://doi.org/10.63125/cz2gwm06

[23]. Feizabadi, J. (2020). Sustainability in humanitarian supply chain: A review. *International Journal of Logistics Research and Applications*. https://doi.org/10.1080/13675567.2020.1803246

[24]. Fosso Wamba, S., Gunasekaran, A., Papadopoulos, T., & Ngai, E. W. T. (2018). Big data analytics in logistics and supply chain management. *The International Journal of Logistics Management*, *29*(2), 478-484. https://doi.org/10.1108/ijlm-02-2018-0026

[25]. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

[26]. Gutjahr, W. J., & Fischer, S. (2018). Equity and deprivation costs in humanitarian logistics. *European Journal of Operational Research*, *270*(1), 185-197. https://doi.org/10.1016/j.ejor.2018.03.019

[27]. Habibullah, S. M., & Aditya, D. (2023). Blockchain-Orchestrated Cyber-Physical Supply Chain Networks with Byzantine Fault Tolerance For Manufacturing Robustness. *Journal of Sustainable Development and Policy*, *2*(03), 34-72. https://doi.org/10.63125/057vwc78

[28]. Hall, D. C., & Saygin, C. (2012). Impact of information sharing on supply chain performance. *The International Journal of Advanced Manufacturing Technology*, *58*, 397-409. https://doi.org/10.1007/s00170-011-3389-0

[29]. Hammad, S. (2022). Application of High-Durability Engineering Materials for Enhancing Long-Term Performance of Rail and Transportation Infrastructure. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 63-96. https://doi.org/10.63125/4k492a62

[30]. Hammad, S., & Muhammad Mohiul, I. (2023). Geotechnical And Hydraulic Simulation Models for Slope Stability And Drainage Optimization In Rail Infrastructure Projects. *Review of Applied Science and Technology*, *2*(02), 01–37. https://doi.org/10.63125/jmx3p851

[31]. Haque, B. M. T., & Md. Arifur, R. (2020). Quantitative Benchmarking of ERP Analytics Architectures: Evaluating Cloud vs On-Premises ERP Using Cost-Performance Metrics. *American Journal of Interdisciplinary Studies*, *1*(04), 55-90. https://doi.org/10.63125/y05j6m03

[32]. Haque, B. M. T., & Md. Arifur, R. (2021). ERP Modernization Outcomes in Cloud Migration: A Meta-Analysis of Performance and Total Cost of Ownership (TCO) Across Enterprise Implementations. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 168–203. https://doi.org/10.63125/vrz8hw42

[33]. Haque, B. M. T., & Md. Arifur, R. (2023). A Quantitative Data-Driven Evaluation of Cost Efficiency in Cloud and Distributed Computing for Machine Learning Pipelines. *American Journal of Scholarly Research and Innovation*, *2*(02), 449–484. https://doi.org/10.63125/7tkcs525

[34]. Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80. https://doi.org/10.1016/j.ijpe.2014.04.018

[35]. Hazen, B. T., Skipper, J. B., Ezell, J. D., & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. *Computers & Industrial Engineering*, *101*, 592-598. https://doi.org/10.1016/j.cie.2016.06.030

[36]. Hofmann, E. (2017). Big data and supply chain decisions: The impact of volume, variety and velocity properties on the decision-making process. *International Journal of Production Research*, *55*(17), 5108-5126. https://doi.org/10.1080/00207543.2015.1061222

[37]. Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2016). On the unique features of post-disaster humanitarian logistics. *Journal of Operations Management*, *45*, 14-28. https://doi.org/10.1016/j.jom.2016.05.008

[38]. Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L. N., & Aros-Vera, F. (2013). On the appropriate objective function for post-disaster humanitarian logistics models. *Journal of Operations Management*, *31*(5), 262-280. https://doi.org/10.1016/j.jom.2013.06.002

[39]. Huang, K., & Rafiei, R. (2019). Equitable last mile distribution in emergency response. *Computers & Industrial Engineering*, *127*, 887-900. https://doi.org/10.1016/j.cie.2018.11.025

[40]. Huang, M., Smilowitz, K., & Balcik, B. (2012). Models for relief routing: Equity, efficiency and efficacy. *Transportation Research Part E: Logistics and Transportation Review*, *48*(1), 2-18. https://doi.org/10.1016/j.tre.2011.05.004

[41]. Jabed Hasan, T., & Waladur, R. (2022). Advanced Cybersecurity Architectures for Resilience in U.S. Critical Infrastructure Control Networks. *Review of Applied Science and Technology*, *1*(04), 146–182. https://doi.org/10.63125/5rvjav10

[42]. Jahangir, S., & Hammad, S. (2024). A Meta-Analysis of OSHA Safety Training Programs and their Impact on Injury Reduction and Safety Compliance in U.S. Workplaces. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 559–592. https://doi.org/10.63125/8zxw0h59

[43]. Jahangir, S., & Muhammad Mohiul, I. (2023). EHS Analytics for Improving Hazard Communication, Training Effectiveness, and Incident Reporting in Industrial Workplaces. *American Journal of Interdisciplinary Studies*, *4*(02), 126-160. https://doi.org/10.63125/ccy4x761

[44]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, *2*(02), 32-66. https://doi.org/10.63125/1p8gbp15

[45]. Kalaitzi, D., & Tsolakis, N. (2022). Artificial intelligence and machine learning in humanitarian logistics: A systematic review and research agenda. *International Journal of Production Economics*, *251*, 108466. https://doi.org/10.1016/j.ijpe.2022.108466

[46]. Kovács, G., & Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. *International Journal of Physical Distribution & Logistics Management*, *37*(2), 99-114. https://doi.org/10.1108/09600030710734820

[47]. Kunovjanek, M., & Wankmüller, C. (2021). Humanitarian logistics and supply chain management: A systematic literature review and directions for future research. *International Journal of Physical Distribution & Logistics Management*, *51*(7), 742-779. https://doi.org/10.1108/ijpdlm-04-2020-0120

[48]. Leiras, A., de Brito Jr, I., Peres, E. Q., Bertazzo, T. R., & Yoshizaki, H. T. Y. (2014). Literature review of humanitarian logistics research: Trends and challenges. *Journal of Humanitarian Logistics and Supply Chain Management*, *4*(1), 95-130. https://doi.org/10.1108/jhlscm-04-2012-0008

[49]. Lu, Y., Yang, C., & Yang, J. (2022). A multi-objective humanitarian pickup and delivery vehicle routing problem with drones. *Annals of Operations Research*, *319*, 291-353. https://doi.org/10.1007/s10479-022-04816-y

[50]. Luo, W., & Qi, Y. (2009). An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. *Health & Place*, *15*(4), 1100-1107. https://doi.org/10.1016/j.healthplace.2009.06.002

[51]. Manupati, V. K., Schoenherr, T., Subramanian, N., Ramkumar, M., Soni, B., & Panigrahi, S. (2021). A multi-echelon dynamic cold chain for managing vaccine distribution. *Transportation Research Part E: Logistics and Transportation Review*, *156*, 102542. https://doi.org/10.1016/j.tre.2021.102542

[52]. Maroufkhani, P., Iranmanesh, M., Ghobakhloo, M., & Nilashi, M. (2020). Big data analytics adoption model for small and medium enterprises. *Journal of Science and Technology Policy Management*, *11*(4), 483-513. https://doi.org/10.1108/jstpm-02-2020-0018

[53]. Masud, R., & Hammad, S. (2024). Computational Modeling and Simulation Techniques For Managing Rail–Urban Interface Constraints In Metropolitan Transportation Systems. *American Journal of Scholarly Research and Innovation*, *3*(02), 141–178. https://doi.org/10.63125/pxet1d94

[54]. Md Ashraful, A., Md Fokhrul, A., & Md Fardaus, A. (2020). Predictive Data-Driven Models Leveraging Healthcare Big Data for Early Intervention And Long-Term Chronic Disease Management To Strengthen U.S. National Health Infrastructure. *American Journal of Interdisciplinary Studies*, *1*(04), 26-54. https://doi.org/10.63125/1z7b5v06

[55]. Md Fokhrul, A., Md Ashraful, A., & Md Fardaus, A. (2021). Privacy-Preserving Security Model for Early Cancer Diagnosis, Population-Level Epidemiology, And Secure Integration into U.S. Healthcare Systems. *American Journal of Scholarly Research and Innovation*, *1*(02), 01–27. https://doi.org/10.63125/q8wjee18

[56]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And Iot Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[57]. Md Harun-Or-Rashid, M., & Sai Praveen, K. (2022). Data-Driven Approaches To Enhancing Human–Machine Collaboration In Remote Work Environments. *International Journal of Business and Economics Insights*, *2*(3), 47-83. https://doi.org/10.63125/wt9t6w68

[58]. Md, K., & Sai Praveen, K. (2024). Hybrid Discrete-Event And Agent-Based Simulation Framework (H-DEABSF) For Dynamic Process Control In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 72–96. https://doi.org/10.63125/wcqq7x08

[59]. Md. Akbar, H., & Farzana, A. (2023). Predicting Suicide Risk Through Machine Learning–Based Analysis of Patient Narratives and Digital Behavioral Markers in Clinical Psychology Settings. *Review of Applied Science and Technology*, *2*(04), 158–193. https://doi.org/10.63125/mqty9n77

[60]. Md. Arifur, R., & Haque, B. M. T. (2022). Quantitative Benchmarking of Machine Learning Models for Risk Prediction: A Comparative Study Using AUC/F1 Metrics and Robustness Testing. *Review of Applied Science and Technology*, *1*(03), 32–60. https://doi.org/10.63125/9hd4e011

[61]. Md. Towhidul, I., Alifa Majumder, N., & Mst. Shahrin, S. (2022). Predictive Analytics as A Strategic Tool For Financial Forecasting and Risk Governance In U.S. Capital Markets. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 238–273. https://doi.org/10.63125/2rpyze69

[62]. Mediavilla, M. (2022). Artificial intelligence methods for demand forecasting: A review. *Procedia CIRP*, *107*, 593-598. https://doi.org/10.1016/j.procir.2022.05.119

[63]. Mostafa, K. (2023). An Empirical Evaluation of Machine Learning Techniques for Financial Fraud Detection in Transaction-Level Data. *American Journal of Interdisciplinary Studies*, *4*(04), 210-249. https://doi.org/10.63125/60amyk26

[64]. Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, *98*, 254-264. https://doi.org/10.1016/j.cor.2017.07.004

[65]. Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, *51*(5), 497-510. https://doi.org/10.1016/j.im.2014.03.006

[66]. Orgut, I. S., Ivy, J. S., Uzsoy, R., & Hale, C. (2018). Robust optimization approaches for the equitable and effective distribution of donated food. *European Journal of Operational Research*, *269*(2), 516-531. https://doi.org/10.1016/j.ejor.2018.02.017

[67]. Parappathodi, J., & Archetti, C. (2022). Crowdsourced humanitarian relief vehicle routing problem. *Computers & Operations Research*, *148*, 105963. https://doi.org/10.1016/j.cor.2022.105963

[68]. Prajogo, D., & Olhager, J. (2012). Supply chain integration and performance: The effects of long-term relationships, information technology and sharing, and logistics integration. *International Journal of Production Economics*, *135*(1), 514-522. https://doi.org/10.1016/j.ijpe.2011.09.001

[69]. Ransikarbum, K., Mason, S. J., & Anderson-Cook, C. (2020). Inventory routing for the last mile delivery of humanitarian relief supplies. *OR Spectrum*, *42*, 1139-1176. https://doi.org/10.1007/s00291-020-00572-2

[70]. Rauf, M. A. (2018). A needs assessment approach to english for specific purposes (ESP) based syllabus design in Bangladesh vocational and technical education (BVTE). *International Journal of Educational Best Practices*, *2*(2), 18-25.

[71]. Reihaneh, M., & Ghoniem, A. (2017). A multi-start optimization-based heuristic for a food bank distribution problem. *Journal of the Operational Research Society*, *68*(12), 1583-1595. https://doi.org/10.1057/s41274-017-0220-9

[72]. Rifat, C., & Jinnat, A. (2022). Optimization Algorithms for Enhancing High Dimensional Biomedical Data Processing Efficiency. *Review of Applied Science and Technology*, *1*(04), 98–145. https://doi.org/10.63125/2zg6x055

[73]. Rifat, C., & Khairul Alam, T. (2022). Assessing The Role of Statistical Modeling Techniques in Fraud Detection Across Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(02), 91-125. https://doi.org/10.63125/gbdq4z84

[74]. Rifat, C., & Rebeka, S. (2023). The Role of ERP-Integrated Decision Support Systems in Enhancing Efficiency and Coordination In Healthcare Logistics: A Quantitative Study. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 265–285. https://doi.org/10.63125/c7srk144

[75]. Rifat, C., & Rebeka, S. (2024). Integrating Artificial Intelligence and Advanced Computing Models to Reduce Logistics Delays in Pharmaceutical Distribution. *American Journal of Health and Medical Sciences*, *5*(03), 01–35. https://doi.org/10.63125/t1kx4448

[76]. Sai Praveen, K. (2024). AI-Enhanced Data Science Approaches For Optimizing User Engagement In U.S. Digital Marketing Campaigns. *Journal of Sustainable Development and Policy*, *3*(03), 01-43. https://doi.org/10.63125/65ebsn47

[77]. Schiffling, S., & Piecyk, M. (2014). Performance measurement in humanitarian logistics: A customer-oriented approach. *Journal of Humanitarian Logistics and Supply Chain Management*, *4*(2), 198-221. https://doi.org/10.1108/jhlscm-08-2013-0027

[78]. Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, *36*(1), 120-132. https://doi.org/10.1111/jbl.12082

[79]. Shehwar, D., & Nizamani, S. A. (2024). Power Dynamics in Indian Ocean: US Indo-Pacific Strategic Report and Prospects for Pakistan's National Security. *Government: Research Journal of Political Science*, *13*.

[80]. Shoflul Azam, T., & Md. Al Amin, K. (2024). Quantitative Study on Machine Learning-Based Industrial Engineering Approaches For Reducing System Downtime In U.S. Manufacturing Plants. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 526–558. https://doi.org/10.63125/kr9r1r90

[81]. Tzeng, G.-H., Cheng, H.-J., & Huang, T. D. (2007). Multi-objective optimal planning for designing relief delivery systems. *Transportation Research Part E: Logistics and Transportation Review*, *43*(6), 673-686. https://doi.org/10.1016/j.tre.2006.10.012

[82]. Van Steenbergen, R., Mes, M., & van Heeswijk, W. (2023). Reinforcement learning for humanitarian relief distribution with trucks and UAVs under travel time uncertainty. *Transportation Research Part C: Emerging Technologies*, *157*, 104401. https://doi.org/10.1016/j.trc.2023.104401

[83]. Van Wassenhove, L. N. (2006). Humanitarian aid logistics: Supply chain management in high gear. *Journal of the Operational Research Society*, *57*(5), 475-489. https://doi.org/10.1057/palgrave.jors.2602125

[84]. Walker, R. E., Keane, C. R., & Burke, J. G. (2010). Disparities and access to healthy food in the United States: A review of food deserts literature. *Health & Place*, *16*(5), 876-884. https://doi.org/10.1016/j.healthplace.2010.04.013

[85]. Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that transforms supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84. https://doi.org/10.1111/jbl.12010

[86]. Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110. https://doi.org/10.1016/j.ijpe.2016.03.014

[87]. Wang, Y.-M., Wang, Y.-S., & Yang, Y.-F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, *77*(5), 803-815. https://doi.org/10.1016/j.techfore.2010.03.006

[88]. Zaman, M. A. U., Sultana, S., Raju, V., & Rauf, M. A. (2021). Factors İmpacting the Uptake of İnnovative Open and Distance Learning (ODL) Programmes in Teacher Education. *Turkish Online Journal of Qualitative Inquiry*, *12*(6).

[89]. Zhang, L., & Cui, N. (2021). Humanitarian logistics and emergencies management: New perspectives to a sociotechnical problem and its optimization approach management. *International Journal of Disaster Risk Reduction*, *52*, 101952. https://doi.org/10.1016/j.ijdrr.2020.101952