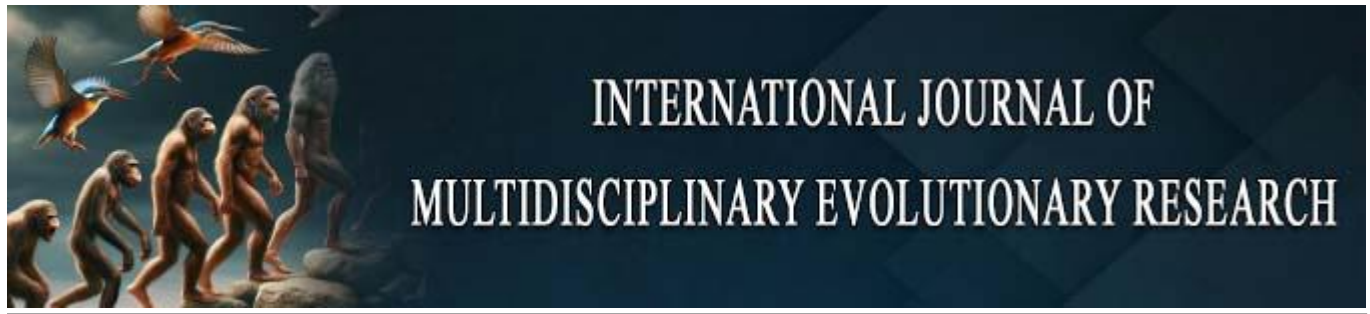




Real-Time Order Visibility for Lead-Time Compression in Global Heavy-Equipment Distribution Networks

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Abstract

Incomplete shipping instructions can leave configured industrial equipment waiting after production is complete. This paper develops a real-time order-visibility design and an evaluation protocol for global heavy-equipment distribution. The design places order status, instruction completeness and shipping exceptions in a shared operating view with named response owners. The protocol separates order-entry, production and post-production intervals and specifies outcomes for lead time, reliability, instruction holds, promised-date performance and inquiry workload. Proposed analyses combine descriptive comparisons, interrupted time series and a suitable comparison group, with explicit attention to censoring, seasonality, adoption and spillovers. The six hypotheses remain untested because order-level estimates are not reported. The contribution is a transparent method for investigating whether information readiness reduces post-production waiting without attributing all changes after rollout to the dashboard. Validation requires dated deployment records, consistent timestamp definitions, usage logs and documented concurrent operational changes. The framework can guide a prospective evaluation and prevent unsupported claims of causal or statistical improvement.

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1. Introduction

Time has long been recognized as a source of competitive advantage in manufacturing and distribution (Stalk, 1988). In consumer goods, lead-time reduction is usually pursued through physical means: faster transport modes, forward-positioned inventory, and leaner production. In heavy-equipment distribution, those levers are expensive and slow to pull. A configured engine cannot be stocked in every region, freight for multi-tonne units is constrained by carrier capacity and export documentation, and production slots are scheduled weeks in advance. As a result, a large share of the controllable lead time in these networks sits not in the factory or on the truck but in the administrative path that connects a customer's order to a shipment leaving the dock.

That administrative path is where visibility matters. A typical engine order passes through order entry, credit review, configuration validation, production scheduling, build, test, packaging, export compliance, and carrier booking. At several points the order depends on information supplied by the customer: the ship-to address, the preferred carrier or freight forwarder, Incoterms, packaging and labeling requirements, consolidation preferences, and delivery windows. When this information is incomplete or changes after order entry, the finished unit waits. The waiting is rarely recorded as a cause in the ERP system. It

shows up instead as a longer order-to-ship interval, a missed promise date, and a stream of emails and calls asking where the order is.

This paper develops a shared order-status and shipping-instruction design informed by a practitioner dashboard deployment. It proposes an evaluation protocol rather than reporting order-level effects. A dashboard rollout alone cannot identify causality: production, transport, inventory and customer changes must also be recorded and assessed.

The contribution distinguishes order-status visibility from shipping-information readiness, specifies a quasi-experimental evaluation protocol and decomposes lead time into administrative, production and post-production intervals. These mechanisms remain hypotheses for empirical testing. The remainder of the paper is organized as follows. Sections 1.1 to 1.5 review the literature on visibility and integration, information latency and lead time, dashboards and analytics, capital-goods distribution and related operational settings. Section 1.6 translates that literature into design choices for the order-visibility framework, and Section 1.7 states the hypotheses. Section 2 describes the research setting, the intervention, the data requirements and the analysis models. Section 3 sets out the proposed evaluation and how its results should be interpreted, and Section 4 concludes.

1.1. Supply Chain Visibility and Integration

Supply chain visibility has been defined in several overlapping ways. Francis (2008a) characterizes it as the identity, location, and status of entities moving through the supply chain, captured in timely messages about events, along with planned dates and times for those events. Barratt and Oke (2007) emphasize that visibility is not simply the existence of shared data but the extent to which actors have access to information that is useful to them, and they argue from a resource-based perspective that visibility yields advantage only when it is embedded in collaborative routines that are difficult to imitate. Caridi, Crippa, Perego, Sianesi, and Tumino (2010) propose a quantitative approach that rates visibility along the dimensions of quantity, quality, and freshness of information, and they show that higher visibility is associated with better supply chain performance.

A recurring theme in this literature is that visibility is a capability that must be converted into action. Williams, Roh, Tokar, and Swink (2013) find that visibility improves supply chain responsiveness and that internal integration moderates this relationship: firms whose functions already coordinate well are better positioned to exploit new information. This finding is important for the present study, because an order-tracking dashboard is primarily an internal integration device. It places the same information in front of functions that previously held different, partial pictures of the same orders. Work on industrial and capital-intensive supply chains reaches a similar conclusion from a different direction. Frameworks for agile supply chain digital transformation stress that new information systems deliver value only when embedded in governed, repeatable processes (Mbonu, Iwuanyanwu, Aliliele, & Uzoka, 2020a). Models for ERP-enabled procurement show how integrating location and transaction data inside the ERP environment improves the timeliness of operational decisions (Ahiaeke Patrick, Okonkwo, Mayo, & Okeke, 2020). Research on supply chain risk and resilience in engineering and gas processing projects further identifies poor information flow between functions as a recurring source of delay and disruption in equipment-

heavy networks (Agbabiaka, Okonkwo, Ogunwole, Mayo, & Okeke, 2019; Ogunwole, Okonkwo, Agbabiaka, Mayo, & Okeke, 2021).

A large body of empirical work links information sharing and supply chain integration to operational performance. Manufacturers that integrated widely with both suppliers and customers achieved the largest gains in delivery and responsiveness (Frohlich & Westbrook, 2001), and later studies confirmed that customer, supplier and internal integration each relate to performance, with internal integration acting as the foundation for the others (Flynn *et al.*, 2010; Huo, 2012; Zhao *et al.*, 2011). Internal and external integration both improve time-based measures such as delivery speed (Droge *et al.*, 2004; Swink *et al.*, 2007), and environmental uncertainty changes the strength of these effects (Wong *et al.*, 2011). Integrative information technology improves customer service and, through it, financial results (Vickery *et al.*, 2003), while digitally enabled integration of information, physical and financial flows yields significant performance gains (Rai *et al.*, 2006). Integration of production information is the channel through which eBusiness technologies improve delivery and flexibility (Devaraj *et al.*, 2007), information technology capability and logistics integration together support better delivery and lead-time performance (Prajogo & Olhager, 2012), and integration and information sharing are both associated with better on-time delivery (Sezen, 2008).

Analytical models explain why shared information matters. Sharing demand and inventory data lowers cost, but the gains from shorter lead times and smaller batches, which information technology makes possible, are larger still (Cachon & Fisher, 2000). The value of shared demand information rises when lead times are long (Lee *et al.*, 2000), order variability grows with lead time even when demand information is centralized (Chen *et al.*, 2000), and coordinated ordering combined with information sharing improves service in capacity-constrained chains (Zhao *et al.*, 2002). Reviews conclude that sharing production information such as lead times, capacity and order status dampens bullwhip effects and improves responsiveness (Huang *et al.*, 2003; Sahin & Robinson, 2002), and that partners can exchange inventory, sales, order-status and forecast data to cut cycle and response times (Lee & Whang, 2000; Yu *et al.*, 2001).

The quality of shared information matters as much as its quantity. Information sharing and information quality, including timeliness, accuracy and reliability, are distinct constructs with distinct drivers (Li & Lin, 2006), and information quality improves performance only when it is matched by suitable supply chain practices (Zhou & Benton, 2007; Zhou *et al.*, 2014). Collaboration research identifies information sharing and synchronized decision making as core dimensions of supply chain collaboration (Cao *et al.*, 2010; Simatupang & Sridharan, 2002) and shows that collaboration creates time-based advantages that raise performance (Cao & Zhang, 2011; Stank *et al.*, 2001). Effective sharing also requires willingness as well as technical connectivity (Fawcett *et al.*, 2007). Studies that address visibility directly find that governance mechanisms create information visibility that improves flexibility (Wang & Wei, 2007), that better visibility of process and order status improves performance when backed by measurement and management practice (Bartlett *et al.*, 2007), that integrating information with downstream customers improves

replenishment outcomes (Kulp *et al.*, 2004), and that firms with greater supply chain visibility outperform comparable firms operationally (Swift *et al.*, 2019).

1.2. Information Latency and Lead Time

Operations management offers a precise way to link information delay to lead time. Little's Law establishes that, in a stable system, the average time an item spends in the system equals the average number of items in the system divided by the throughput rate (Little, 1961). Hopp and Spearman (2011) show how cycle time in a production or order system decomposes into processing time, move time, queue time, and wait-to-match time, and they observe that queue and waiting components typically dominate. An order that is physically complete but awaiting a shipping instruction is in a wait-to-match state: the unit is ready, the information is not. Reducing the time until the missing information is detected and supplied therefore reduces lead time without any change in processing capacity.

The bullwhip literature provides a complementary perspective. Lee, Padmanabhan, and Whang (1997) show that distorted and delayed information propagates and amplifies through supply chains, producing variability that is out of proportion to underlying demand. Although that work concerns demand signals, the same logic applies to order-status signals. When status information reaches customers late or inconsistently, customers respond with inquiries, expedite requests, and order changes, which in turn consume capacity and lengthen the cycle for other orders.

Evidence from logistics operations in emerging and energy-sector settings points to the same pattern. Okonkwo, Agbabiaka, Ogunwole, Mayo, and Okeke (2020) show that demurrage and port delays stem largely from late or incomplete documentation and weak coordination among shippers, forwarders, and port operators rather than from physical handling capacity. Related work on materials readiness finds that supply chain performance depends on whether the information needed to release materials is complete when the physical item becomes available (Okonkwo, Agbabiaka, Ogunwole, Mayo, & Okeke, 2021), and models of inventory availability link plant uptime to the visibility of stock and replenishment status (Okonkwo, Ogunwole, & Okeke, 2018b). These findings parallel the wait-to-match logic above: goods that are physically ready still wait when the information that releases them is missing. The case for lead-time reduction as a strategic lever is well established. Reviews of time-based competition treat lead-time compression as a competitive weapon (Hum & Sim, 1996; Tersine & Hummingbird, 1995), and time-based manufacturing practices are linked to mass customization capability and customer value (Tu *et al.*, 2001). Time-compression research shows that information and decision delays, not only material delays, account for much of total cycle time (Mason-Jones & Towill, 1999; Towill, 1996), and that lead-time reduction can improve demand chain performance more than better demand information alone (de Treville *et al.*, 2004). Agile supply chains respond to real demand through shared information (Christopher, 2000), and combining lean upstream with agile downstream practices balances cost against responsiveness (Naylor *et al.*, 1999). Quick response manufacturing extends this logic to office and order-processing work by attacking queue time (Suri, 1998), while lean thinking classifies waiting between value-adding steps as waste (Womack & Jones, 1996).

Queueing theory explains why waiting dominates lead time. Waiting rises steeply as utilization approaches capacity and as variability increases (Kingman, 1961), lead times depend on workload and batch size through queueing effects (Karmarkar, 1987), and limiting work in process yields shorter and more predictable cycle times (Hopp & Spearman, 2004; Spearman *et al.*, 1990). Research on lead-time quotation shows that due dates set from real-time system status can meet service targets while quoting shorter lead times (Duenyas & Hopp, 1995; Hopp & Roof Sturgis, 2000), and that variability in delivery timing carries measurable cost (Guiffrida & Nagi, 2006).

Order fulfillment is a cross-functional process whose performance depends on coordinating its subprocesses (Croxtton, 2003). Responsiveness depends on how quickly order information is captured and acted upon, not only on production capability (Kritchanai & MacCarthy, 1999), and redesigning information flows in order fulfillment cuts cycle times and improves due-date performance (Lin & Shaw, 1998). Make-to-order firms with competitive lead times communicate and schedule more closely with customers (Handfield & Pannesi, 1995), and supply chains with stronger information processing achieve shorter cycle times (Hult *et al.*, 2004). In configure-to-order settings, the position of the customer order decoupling point determines how much order-driven lead time the customer must absorb (Olhager, 2003, 2010; Rudberg & Wikner, 2004; Wikner & Rudberg, 2005). Build-to-order research identifies information technology and coordinated order handling as key enablers (Gunasekaran & Ngai, 2005), product configuration systems reduce order errors and time to fulfillment (Forza & Salvador, 2002), and studies of vehicle supply show that scheduling and order-handling practice adds large delays to order-to-delivery time (Holweg *et al.*, 2005; Pil & Holweg, 2004). Order lead time and delivery reliability are accordingly among the core metrics of supply chain performance (Gunasekaran *et al.*, 2001).

1.3. Dashboards and Analytics in Order Management

Dashboards are among the most widely adopted business intelligence artifacts, yet their operational effects are less often measured than their adoption. Few (2006) describes an effective dashboard as a single-screen display of the most important information needed to achieve objectives, arranged so it can be monitored at a glance. In an order-management context, that definition implies a small number of exception views (orders at risk, instructions missing, promise dates approaching) rather than a comprehensive report. Reviews of digital transformation in operations management similarly report that analytics tools produce measurable gains mainly when paired with process redesign (Agboada, Ezeako, Okoli, & Uzodu, 2018), and business intelligence architectures that prioritize risk-relevant indicators help managers focus on exceptions instead of routine volume (Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2021a). Prior evaluations of visibility technologies in logistics have focused heavily on shipment tracking after dispatch. Less attention has been given to visibility of the pre-shipment order cycle, and to customer-side information such as shipping instructions, which is the focus of this study.

Related work on business intelligence supports this exception-oriented view. Sanni and Atima (2021b) describe dashboard frameworks built to close executive visibility gaps, arguing that the value of a dashboard lies in exposing

the few indicators that call for a decision. Analytics-driven operating frameworks likewise show how consolidated data can be turned into repeatable decision routines across complex, multi-party processes (Sanni & Atima, 2021a). Real-time monitoring architectures from enterprise log analytics show the same logic in a technical setting, where events are streamed, filtered and escalated automatically rather than reviewed in bulk (Mbonu, Iwuanyanwu, Uzoka, & Oluoha, 2019). Research on industrial safety offers a useful parallel. Data-driven risk-control models for large energy projects (Obriki & Arumosoye, 2018) and studies of near-miss and hazard-observation data (Arumosoye & Obriki, 2019) both show that leading indicators prevent costly outcomes only when they are captured systematically and reviewed before the event. A missing shipping instruction flagged before a unit is built works the same way, as a leading indicator of delay.

Dashboards sit within a broader tradition of performance measurement, which defines measurement as quantifying the efficiency and effectiveness of action (Neely *et al.*, 1995) and treats measurement systems as tools for monitoring, communication and influencing behavior (Franco-Santos *et al.*, 2007). Reviews of dashboards in performance management show that their effectiveness depends on design choices matched to purpose and users (Yigitbasioğlu & Velcu, 2012). Display design matters in its own right: people judge position along a common scale more accurately than area or angle (Cleveland & McGill, 1984), and decisions are faster and more accurate when the format of information fits the task (Vessey, 1991). Decision support research traces the move from model-based systems to data warehousing and web-based tools that give managers current operational data (Arnott & Pervan, 2005; Shim *et al.*, 2002).

Evidence on business intelligence and analytics points to operational as well as financial gains. Business intelligence systems produce measurable process-level benefits (Elbashir *et al.*, 2008) and have evolved from reporting toward analytics capable of large business impact (Chen *et al.*, 2012). Business analytics is associated with better supply chain performance across plan, source, make and deliver processes (Trkman *et al.*, 2010), and analytics capability built from technology, management and talent improves firm performance (Aker *et al.*, 2016; Gupta & George, 2016; Wamba *et al.*, 2017). Connectivity and information sharing support the assimilation of predictive analytics (Gunasekaran *et al.*, 2017), analytics in logistics ranges from descriptive views of order flows to strategic applications (Waller & Fawcett, 2013; Wang *et al.*, 2016), and supply chain visibility strengthens analytics capability and its link to operational performance (Srinivasan & Swink, 2018). These benefits rest on information technology capability as a firm resource (Bharadwaj, 2000) and on the enterprise systems that supply the data. ERP adoption has been followed by improvements in lead time and on-time delivery after a short implementation dip (McAfee, 2002), is associated with improved profitability (Hendricks *et al.*, 2007), and yields plant-level coordination benefits that are largest where units are interdependent (Gattiker & Goodhue, 2005).

Whether a dashboard delivers these benefits depends on data quality and use. Data consumers judge quality on timeliness, accessibility and representation as well as accuracy (Wang & Strong, 1996), quality can be assessed with objective metrics such as completeness (Pipino *et al.*, 2002), and poor data quality undermines supply chain analytics (Hazen *et al.*,

2014). Information quality leads to better decisions only within a culture of analytical decision making (Popovič *et al.*, 2012). Information systems success models link system, information and service quality to use, satisfaction and net benefits (DeLone & McLean, 1992, 2003), and technology acceptance research shows that perceived usefulness, ease of use, job relevance and facilitating conditions determine whether people actually use a system (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh *et al.*, 2003).

1.4. Capital-Goods Distribution

Capital-goods supply chains differ from high-volume consumer chains in ways that raise the value of visibility. Order volumes are lower, unit values are higher, products are frequently configured, and lead times are long enough that customers plan their own production around promised dates. An OEM building generators, construction equipment, or marine vessels cannot complete its own assembly without the engine. A late engine therefore carries a cost far larger than its own margin. Christopher (2016) argues that in such settings the network should be managed as an information system first and a physical system second, because information is the cheaper lever. Studies of procurement and supply management in oil, gas and energy operations, which share many traits with heavy-equipment distribution, support this view. They show that delay and cost in capital-intensive networks often come from weak information flow among buyers, vendors and logistics providers. Frameworks for strategic procurement optimization (Okonkwo, Ogunwole, & Okeke, 2018a), vendor governance and contract management (Okonkwo, Ogunwole, Okeke, & Mayo, 2019), and data-driven vendor evaluation (Ahiaekwe Patrick, Okonkwo, Mayo, & Okeke, 2021) all treat timely, shared information as a precondition for performance. Work on regulatory-compliant procurement in high-risk environments shows how compliance checks can become hidden sources of waiting time when documentation is incomplete (Okonkwo, Ogunwole, Mayo, & Okeke, 2021), which applies directly to export shipments of engines. Research on coordinating processes across multiple stakeholders (Eyetsemitan, Ambali, Oyeleye, & Fadayomi, 2020) and on managing programs across many sites (Aminu-Ibrahim, Ogbete, & Ambali, 2021) further highlights the coordination problems that arise when plants, regions and customers work from different information. Despite this, empirical before-and-after evidence on the lead-time effects of order visibility in heavy-equipment distribution remains limited. This paper responds to that gap by specifying the design and the evaluation protocol through which such evidence can be produced. In upstream petroleum projects, misalignment between capital budgeting and field development execution has been traced partly to long-lead equipment and logistics feasibility being considered after sanction rather than within it (Nwangwu *et al.*, 2021), a reminder that late information about configured, high-value items carries costs well beyond the warehouse.

Research on capital goods and after-sales supply chains documents the conditions that make visibility valuable. Benchmarks of service parts logistics among capital equipment makers reveal wide gaps in response times (Cohen *et al.*, 1997), and spare parts networks for industrial equipment face erratic demand and high downtime costs that shape network design (Huiskonen, 2001; Wagner *et al.*, 2012). After-sales supply chains are configured across

manufacturers, distributors and dealers in ways that govern information flow (Saccani *et al.*, 2007), and their performance requires measurement frameworks that span these actors (Gaiardelli *et al.*, 2007). Engineer-to-order chains combine long lead times with tailored orders, yet research on coordination and information in such settings remains limited (Gosling & Naim, 2009). For export shipments the stakes are high: each day of delay before shipment, including time lost to documents and procedures, reduces trade (Djankov *et al.*, 2010), each day in transit carries a cost equal to a meaningful share of goods value (Hummels & Schaur, 2013), and logistics performance, including export documentation and clearance, is linked to trade volumes (Hausman *et al.*, 2013).

1.5. Related Evidence from Other Operational Settings

Studies of industrial safety management offer a close analogue to lead-time control, because both depend on detecting weak signals before they become costly events. Conceptual models of heat stress risk (Arumosoye & Obriki, 2018), contractor safety governance (Arumosoye & Obriki, 2020), human error causation (Obriki & Arumosoye, 2020) and management safety walkthroughs (Obriki & Arumosoye, 2019) all stress structured observation and timely feedback. Work on operational integrity in high-risk drilling shows how productivity and compliance can be balanced through disciplined monitoring (Nwangwu *et al.*, 2018). Reviews of internal audit systems (Obogo, Arumosoye, & Obriki, 2020a), heavy-lift risk management (Obogo, Arumosoye, & Obriki, 2020b), safety systems in maintenance projects (Obogo, Arumosoye, & Obriki, 2020c), near-miss reporting (Obogo, Arumosoye, & Obriki, 2021) and incident prevention in maintenance engineering (Obogo, Obriki, & Arumosoye, 2021) emphasize that indicators improve outcomes only when reports reach the people able to act on them quickly. Studies of construction safety culture, risk governance and hazard control (Obogo, Ozobu, & Uduokhai, 2019a, 2019b; Obogo, Uduokhai, & Ozobu, 2019, 2021) and of institutionalizing safe practice across project organizations (Obriki & Arumosoye, 2021) reach a similar conclusion about the role of shared, routine visibility in multi-party operations.

Research on healthcare infrastructure delivery provides a further analogy in throughput and coordination. Laboratory spatial planning affects clinical throughput (Ogbete *et al.*, 2018), regulatory-compliant design systems govern how work flows in controlled environments (Ogbete *et al.*, 2019), and materials and energy choices shape facility performance (Ogbete *et al.*, 2020). Studies of risk-managed construction (Ogbete *et al.*, 2021), sustainable laboratory infrastructure (Aminu-Ibrahim *et al.*, 2018), capital project delivery (Aminu-Ibrahim *et al.*, 2019) and infrastructure-driven expansion of diagnostic access (Aminu-Ibrahim *et al.*, 2020) show that multi-site programs depend on reliable status information to keep schedules on track.

Because order dashboards consolidate commercially sensitive data, research on data protection and IT governance is also relevant. Reviews of data protection regulation across jurisdictions (Mbonu, Aliliele, Uzoka, & Oluoha, 2019), identity and access management in hybrid cloud environments (Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2020), infrastructure-as-code governance (Mbonu, Iwuanyanwu, Aliliele, & Uzoka, 2020b) and forensic analytics for compliance monitoring (Mbonu, Iwuanyanwu,

Aliliele, & Uzoka, 2021) describe controls that keep shared data accurate and appropriately restricted. Assessments of cyber risk maturity (Fadero *et al.*, 2021), predictive analytics for transaction monitoring (Atakpa, 2021) and integrated governance frameworks for financial-crime prevention (Fadayomi *et al.*, 2021) show how real-time monitoring and exception flags can be designed to act on risk early, a principle that carries over to order exceptions.

Infrastructure monitoring research illustrates the value of near-real-time status data across dispersed assets. Studies of UAV integration into grid inspection (Dagodzo, 2018a), transmission line inspection methods (Dagodzo, 2018b), remote-sensing interpretation (Dagodzo, 2018c), pipeline and corridor monitoring (Dagodzo & Ahiaekwe Patrick, 2020) and integrated UAV, LiDAR and GIS corridor management (Dagodzo & Ahiaekwe Patrick, 2021b) show how consolidating dispersed observations into one view supports faster intervention.

Similar lessons appear in agricultural and commercial settings. Research on agribusiness finance (Michael & Ogunsola, 2019a), agribusiness education (Michael & Ogunsola, 2019b), policy alignment (Michael & Ogunsola, 2021a), digital agriculture tools (Michael & Ogunsola, 2021b), climate-smart practices (Michael & Ogunsola, 2021d) and extension services (Michael & Ogunsola, 2021e) shows how access to timely information shapes adoption and performance among dispersed actors. In marketing, integrated communications have been linked to customer growth (Agyei *et al.*, 2018) and data-driven positioning helps firms differentiate in complex markets (Sanni *et al.*, 2020b), while translating regulatory requirements into routine workflows depends on clear, standardized process information (Eyetsenitan *et al.*, 2021).

1.6. Design Implications for Order Visibility

The literature reviewed above leaves four design questions open for an engine-order dashboard: which records count as visibility rather than mere data exchange, how a flagged instruction gap is converted into a response, how functions with different incentives agree on who acts, and which measures reveal whether faster shipment has simply moved work or cost elsewhere. The subsections below answer each question with reference to work that addresses it directly. The common starting point is the agile supply chain transformation framework of Mbonu *et al.* (2020a), which ties digital integration to IT risk and compliance controls. For order tracking, that link implies recording the source system and timestamp of every status update and naming the function that resolves conflicting records, so that the lead-time intervals defined in Section 2.3 can later be reconstructed from auditable events rather than from manually maintained spreadsheets.

1.6.1. Visibility Versus Information Sharing

Information sharing and visibility are related but separable design problems. Baah *et al.* (2021) examine visibility, agility and collaboration as channels through which information sharing affects supply chain performance, and Koçoğlu *et al.* (2011) examine how supply chain integration shapes information sharing in the first place; together they suggest that an engine-order dashboard should be judged by whether shared records become usable signals, not by the number of fields exchanged. Lee, Kim, and Kim (2014) relate the visibility provided by interorganizational information

systems to supply chain performance, and Goswami, Engel, and Krcmar (2013) compare information visibility in two supply chain management information systems, a reminder that two systems holding the same order can expose it very differently. Francis (2008b) traces how inconsistently the term visibility is used, which is why the present framework defines each displayed instruction element (ship-to, carrier or forwarder, Incoterms, packaging and labeling, and delivery window) with an explicit completeness rule rather than a generic status flag. Maghsoudi and Pazirandeh (2016) study visibility and resource sharing among humanitarian practitioners, a setting in which partners also act on partial information under time pressure.

The direction of sharing and the incentives behind it also matter. Han, Huo, and Zhao (2021) ask who benefits from backward supply chain information sharing, and Manatsa and McLaren (2008) use agency theory to guide the design of incentives for sharing; both questions bear on the shipping-instruction panel, because the customer supplies the missing data while the manufacturer bears most of the cost of a finished engine waiting at the dock. Kembro and Selviaridis (2015) explain information sharing in the extended supply chain through interdependence among partners, Kim, Hwang, and Rho (2015) examine the moderating role of supply chain culture in the performance effect of RFID utilization and information sharing, and Ruel, Evrard-Samuel, and Vignard (2013) examine collaboration and information sharing within an internal supply chain. These studies support two choices in the present design: every request for a missing instruction is issued by a named customer-service owner, and actual use of the dashboard is measured rather than assumed.

1.6.2. Disruption Risk and Escalation

A missing shipping instruction is a small but frequent disruption, and the disruption literature indicates that detection without response capacity has limited value. Parast and Subramanian (2021) examine how disruption risk drivers affect organizational performance in Chinese supply chains, and Rahman *et al.* (2021) use a data-fusion technique to generate a cyber resilience index for an additive manufacturing supply chain. Both treat a risk measure as an input to managerial action rather than as an outcome in its own right. The framework applies that principle at the level of the order line. Each exception view is paired with an owner, an escalation threshold expressed in days before the promised ship date and a closure record, so that the evaluation can test whether flagged gaps were resolved earlier rather than merely displayed. The same logic underlies the port-logistics model of Okonkwo *et al.* (2020), in which demurrage is traced to late documentation and weak coordination rather than to handling capacity; an engine held for a forwarder nomination is the factory-side equivalent of a container held for missing papers.

1.6.3. Behavioral and Cross-Functional Coordination

An order dashboard redistributes information among order management, plant scheduling, logistics and customer service, each of which is rewarded for different outcomes. Knemeyer and Naylor (2011) argue that behavioral experiments can expand understanding of logistics and supply chain decision making, and their argument applies here because the hypothesized mechanism depends on whether staff act on a flag, not only on whether the flag is

shown. Saleh and Roslin (2015) propose supply chain relational capital as an enabler of integration strategy, which points to the customer relationship as a condition for obtaining complete shipping instructions early in the order cycle. The framework therefore makes decision rules explicit: customer service owns the instruction-gap review, logistics owns the ready-to-ship exception review, and disputed records follow a documented escalation route. These rules also give the evaluation observable behaviors, such as the time from a flag to first customer contact and the time from contact to confirmed instructions, which can be linked to the dated exception actions discussed in Section 3.2.

1.6.4. Linked Performance Measures

Lead time can be compressed by shifting cost or work to another function, so a single speed measure cannot show whether the order cycle as a whole has improved. Anvari (2021) studies how integrating lean, agile, resilient and green supply chain paradigms relates to sustainable supply chain performance, Kim and Schoenherr (2018) examine the effects of supply chain integration on the cost efficiency of contract manufacturing, and Tigga, Kannabiran, and Arumugam (2021) explore relationships among IT advancement, IT assimilation, supply chain capabilities and supply chain performance. Read together, these studies caution against judging an information system on one outcome, or crediting performance to the technology without asking how far it has been assimilated into routines. The framework accordingly pairs order-to-ship duration with its dispersion, instruction holds, promised-date performance and inquiry and expedite workload (Table 2), and Section 2.1 requires concurrent changes in capacity, carrier contracts, inventory policy and customer mix to be documented before any difference is attributed to the dashboard.

1.7. Hypotheses

Order-to-ship lead time can be treated as the sum of a physical component, governed by build, test and pack time, and an informational component, governed by the time orders spend waiting for decisions or data; the second component corresponds to the queue and wait-to-match elements of cycle time (Hopp & Spearman, 2011). The dashboard is expected to act on the informational component through three mechanisms. The first is early detection of shipping-instruction gaps. When instruction completeness is displayed alongside order status, missing or conflicting instructions are identified at order entry or scheduling rather than at the dock, so the request to the customer is issued while the unit is still being built and the wait overlaps with production instead of following it. The second is reduced handoff latency. A shared view removes the need for order management, logistics and plant teams to reconcile separate reports, so status changes reach downstream functions as they occur and the interval between a unit becoming ready and a carrier being booked shortens; this is the internal-integration channel through which visibility is expected to improve responsiveness (Williams *et al.*, 2013). The third is a lower inquiry and expedite load. When customer-facing staff can answer status questions immediately, fewer inquiries are escalated, fewer manual expedites are triggered, and capacity previously consumed by status chasing returns to order processing, reversing in miniature the amplification of delayed signals described by Lee, Padmanabhan, and Whang (1997). These mechanisms lead to the following hypotheses.

H1. Mean order-to-ship lead time is lower after dashboard deployment than before.

H2. Order-to-ship lead-time dispersion, measured by the standard deviation and interquartile range, is lower after deployment. The 90th-percentile lead time is a separate upper-tail outcome.

H3. The share of order lines with complete shipping instructions at production release is higher after deployment, and the incidence of instruction-related shipment holds is lower.

H4. On-time-to-promise performance is higher after deployment.

H5. The volume of customer status inquiries and internal expedite requests per hundred order lines is lower after deployment.

H6. The reduction in lead time is concentrated in the post-build waiting interval (ready-to-ship to actual ship) rather than in the build interval, consistent with an informational rather than physical mechanism.

Hypothesis H6 is central to the identification strategy. If lead time fell because of a concurrent change in production capacity or staffing on the shop floor, the build interval should shrink. If it fell because of improved visibility, the reduction should appear mainly in the interval between a unit being ready and the unit shipping, and in the share of orders held for instructions.

2. Research Method

2.1. Research Setting and Intervention

Cummins Inc. designs, manufactures, distributes, and services diesel and natural gas engines, power generation systems, and related components, serving OEM customers in on-highway, off-highway, power generation, marine, and industrial markets worldwide. Engine orders are fulfilled from multiple plants and routed through a mix of direct OEM shipments, distributor channels, and export movements. Before the intervention, open-order status was available in the ERP system, but shipping instructions were held in a combination of customer master data, order-header text, email correspondence, and regional tracking spreadsheets. Shipping lead time was reported periodically and in aggregate, which made it difficult to see which orders, customers, or lanes were driving delay.

The global sales order tracking dashboard was designed and built by the first author to consolidate order information for engine products into a single, regularly refreshed view. At its core was a line-level open-order view showing order date, requested date, promised ship date, current status, plant, product family, customer and destination region. Alongside it, a shipping-instruction panel indicated whether each required element (ship-to, carrier or forwarder, Incoterms, packaging and labeling, and delivery window) was present and confirmed, and flagged missing or conflicting entries. Shipping lead-time measures, including the order-to-ship, release-to-ready and ready-to-ship intervals, were displayed by plant, product family, region and customer with rolling trend lines. Exception views highlighted orders approaching their promise date with incomplete instructions, units built and awaiting instructions, and orders whose lead time exceeded a threshold for their product family. Filters and drill-downs allowed customer service representatives to answer status questions directly and allowed managers to

identify recurring sources of delay by customer or lane.

The proposed operating routine assigns customer service the instruction-gap review and logistics the ready-to-ship exception review. Evaluation must document actual adoption and concurrent changes in capacity, transport contracts, inventory policy and customer mix, rather than assuming those factors remained constant.

Because the dashboard showed customer names, destinations and commercial terms, access was limited by role, in line with established principles for governing enterprise data protection (Mbonu, Aliliele, Iwuanyanwu, & Oluoha, 2018). Before go-live, the dashboard's figures were reconciled against ERP source tables, and the reconciliation was repeated after each data-model change. This reflects the automated regression-control practice recommended for keeping analytical systems reliable as they evolve (Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2021b).

2.2. Research Design

The evaluation is designed as a quasi-experiment because the dashboard was introduced as an operational change rather than randomly assigned to orders, customers or plants. Shadish, Cook, and Campbell (2002) catalogue the threats that such designs must address; history (a concurrent change in capacity, carrier contracts or customer mix) and instrumentation (a change in how holds, inquiries or timestamps are logged) are the two most relevant to an order dashboard. Ho *et al.* (2017) stress that causal claims in operations management depend on stating the identifying assumption that substitutes for randomization. Two complementary designs are proposed. The first is a single-series interrupted time series in which weekly outcomes before deployment supply the counterfactual trend, and segmented regression separates an immediate level change from a change in slope (Kontopantelis *et al.*, 2015; Lopez Bernal *et al.*, 2017; Wagner *et al.*, 2002). The second is a difference-in-differences comparison between order lines exposed to the dashboard and a comparison group, such as product families or plants not yet covered, observed over the same calendar weeks (Angrist & Pischke, 2009; Imbens & Wooldridge, 2009). Its identifying assumption is that, without the dashboard, both groups would have followed parallel lead-time trends, an assumption that pre-period data can probe but cannot prove.

Pre-deployment, adoption and post-deployment windows should be fixed from dated rollout records before outcomes are extracted, with each window long enough to cover seasonal variation in engine demand and to provide adequate statistical power. Order-to-ship duration is designated as the primary outcome; tests of the secondary hypotheses should be adjusted for multiplicity, and lead-time dispersion should be reported separately from upper-tail levels such as the 90th percentile. All groups must share one time-zone convention and one set of event definitions; durations are measured in calendar days, with working-day durations reported as a sensitivity analysis. Baseline workload, product mix and staffing belong in the confounding assessment, whereas dashboard-induced changes in exception handling are potential mediators and should not be controlled away when the total effect of deployment is estimated. No observation-window lengths or effect estimates are asserted in this manuscript.

2.3. Data and measures

The proposed unit of analysis is the eligible engine order line, linked across order, production, shipment and dashboard records through the order and line identifiers held in the ERP system. Table 1 lists the extraction specification. Inclusion rules and the extraction date must be prespecified. Eligible open orders should remain in the dataset with right-censoring recorded, because restricting the sample to shipped lines removes the longest-waiting orders at the cutoff and biases lead-time comparisons toward shorter durations. Cancelled

orders require separate reporting and, where appropriate, competing-risk analysis. Internal transfers and service replacements should be classified consistently across periods. Because every lead-time component is defined by an ERP event, the extraction should also report the completeness and timeliness of each timestamp field, two of the data-quality dimensions emphasized by Wang and Strong (1996) and measurable with the objective metrics proposed by Pipino *et al.* (2002).

Table 1: Data extraction and sample specification

Dimension	Required extraction specification
Windows	Prespecified dates, rollout and adoption interval
Population	Eligible engine order lines including open orders
Coverage	Customers, plants, regions and product families
Status	Shipment, cancellation and censoring date
Comparability	Export share, order size and baseline instruction gaps

Table 1 specifies the required data; no sample counts or observed outcomes are reported.

Table 2 defines the outcome and control variables and maps each to its hypothesis. Lead-time intervals are measured in calendar days from system timestamps. Table 2 lists the two

post-release components used to test H6; the entry-to-release interval runs from order entry to production release and completes the decomposition shown in Table 3, so that the three components sum to the order-to-ship interval for every shipped line.

Table 2: Variable definitions

Variable	Definition	Hypothesis
Order-to-ship lead time	Days from order entry to goods issue	H1, H2
Release-to-ready	Days from production release to unit available for shipment	H6
Ready-to-ship	Days from unit available to goods issue	H6
Instruction completeness at release	Share of lines with all required instruction elements confirmed at production release	H3
Instruction hold rate	Share of lines placed on hold at the dock for missing or conflicting instructions	H3
On-time-to-promise	Share of lines shipped on or before the promised ship date	H4
Inquiry rate	Customer status inquiries per 100 lines (from case or email logs)	H5
Expedite rate	Internal expedite requests per 100 lines	H5
Controls	Product family, plant, region, export flag, order size, plant load index, month	All

2.4. Data analysis

Descriptive analysis should report means, medians, tail quantiles and rate differences with uncertainty. Welch comparisons and rank-based comparisons offer different estimands (Welch, 1947; Mann & Whitney, 1947); a rank test is not automatically a test of median differences. Completed-order summaries should be accompanied by censoring-aware duration analysis. Weekly interrupted time-series analysis is proposed as follows:

$$LT_t = \beta_0 + \beta_1 \text{time}_t + \beta_2 \text{post}_t + \beta_3 \text{time-after}_t + \gamma X_t + \varepsilon_t \quad (1)$$

where LT is mean weekly order-to-ship lead time, time is a week counter, post is an indicator equal to one after deployment, time-after counts weeks since deployment, and X is a vector of controls. The coefficient β_2 captures the immediate level change and β_3 the change in slope. Newey-West standard errors would be used to account for autocorrelation (Linden, 2015; Newey & West, 1987). The difference-in-differences model at order-line level is:

$$LT_i = \alpha + \delta_1 \text{treated}_i + \delta_2 \text{post}_i + \delta_3 (\text{treated}_i \times \text{post}_i) + \gamma X_i + \varepsilon_i \quad (2)$$

The interaction coefficient is a candidate effect estimate only if the comparison design satisfies its identifying assumptions. Clustering must follow the rollout and dependence structure; customer clustering alone may not capture plant-level shocks (Bertrand *et al.*, 2004; Cameron & Miller, 2015). Pre-period plots and event studies assess trends, but an insignificant pre-trend test does not establish parallel trends. Staggered adoption and spillovers require appropriate estimators and sensitivity analysis.

3. Proposed Evaluation and Discussion

3.1. Before-and-After Assessment

Table 3 specifies the outcome comparisons needed to assess hypotheses H1 to H5 and the duration decomposition needed for H6. Each row pairs an outcome with its estimand and with the reporting a reader would need to judge it. Estimates will require deployment data.

Table 3: Outcome analysis and reporting plan

Outcome	Estimand	Required reporting
Order-to-ship duration	Mean, median and tail quantiles	Censoring-aware estimates and uncertainty
Duration components	Entry-to-release; release-to-ready; ready-to-ship	Timestamp reconciliation and component changes
Instruction readiness and holds	Rates with explicit denominators	Absolute changes and confidence intervals
Promised-date performance	Rate under a frozen promise-date rule	Missing dates and revised promises
Inquiry and expedite workload	Events per 100 eligible order lines	Logging completeness and rate changes

For each outcome, the evaluation should report absolute changes, relative changes where meaningful and measures of uncertainty. No estimates are reported here.

H1 and H2 concern the location and dispersion of order-to-ship duration. Their evaluation should prespecify mean, median and tail-quantile estimands and compare distributions under consistent inclusion and censoring rules. A simple before-and-after contrast is the weakest of the proposed comparisons, because any concurrent change in plant load, carrier capacity or customer mix is absorbed into the estimate (Shadish *et al.*, 2002); it should be reported descriptively and interpreted only alongside the designs in Sections 3.3 and 3.4. A reduction in long-duration orders would be consistent with exception handling, but would not alone establish that mechanism.

H3, H4 and H5 require dated records of instruction completeness, dock holds, promised dates, inquiries and expedites. Denominators and rate changes should be reported consistently. Because order lead time and delivery reliability are distinct performance dimensions (Gunasekaran *et al.*, 2001), H4 should be assessed under a promise-date rule frozen at order acknowledgment, so that revised promises cannot inflate on-time performance. Missing or changed logging practices can produce apparent improvement, so data capture must be audited before hypothesis tests are interpreted.

3.2. Lead-Time Decomposition and Mechanisms

H6 can be evaluated by decomposing order-to-ship time into entry-to-release, release-to-ready and ready-to-ship intervals. The decomposition rests on the distinction between processing time and waiting time in cycle-time analysis

(Hopp & Spearman, 2011): release-to-ready captures build, test and packaging, while ready-to-ship captures the wait-to-match state in which a finished unit awaits instructions or a carrier booking. Timestamp definitions must be consistent, monotonic and reconciled to the total interval, and lines with out-of-sequence events should be reported rather than silently dropped. By Little's Law (Little, 1961), a shorter ready-to-ship interval at stable throughput should also appear as fewer finished units held at the dock, which offers a check on the timestamp-based estimate that does not depend on the same event fields. A decline in waiting with stable production duration would support the proposed informational mechanism, subject to confounding and measurement checks. No decomposition estimates are reported here.

The candidate mechanism is earlier detection and resolution of missing shipping information. Support would require linked evidence that instruction readiness at production release rises before post-production waiting declines, with limited change in physical build time. Adoption logs and dated exception actions can help distinguish information availability from actual use, which matters because visibility is expected to yield advantage only when it is embedded in operating routines (Barratt & Oke, 2007).

3.3. Interrupted Time-Series Specification

Table 4 lists the terms of the weekly interrupted time-series model specified in Section 2.4, the interpretation of each term and the diagnostic each requires. The specification follows the segmented-regression approach of Wagner *et al.* (2002) and the applied guidance of Lopez Bernal *et al.* (2017) and Linden (2015).

Table 4: Interrupted time-series terms and interpretation

Term	Interpretation	Diagnostic
Time	Pre-rollout weekly trend	Adequate observations and seasonality
Post	Immediate level change	Concurrent shocks and adoption timing
Time after	Change in post-rollout slope	Persistence and functional form
Controls and residuals	Measured operating conditions	Autocorrelation and model sensitivity

Table 4 gives an estimation specification, not fitted coefficients.

The level and slope terms distinguish an immediate change from gradual adoption. If staff adopt the exception views over several weeks, a change in slope without a large change in level is the pattern the informational mechanism would predict, whereas an abrupt level shift coinciding with go-live would warrant a search for concurrent events. Seasonal terms, concurrent shocks, autocorrelation and sufficient pre- and post-period observations must be assessed (Kontopantelis *et al.*, 2015). The adoption interval can be

excluded or modeled separately so that partially exposed weeks do not dilute the estimate. Neither a significant level change nor a negative slope, by itself, attributes the change to dashboard use.

3.4. Difference-In-Differences Specification

Table 5 sets out the assumptions under which the interaction coefficient δ_3 in the order-line model of Section 2.4 can be read as an effect estimate, together with the diagnostic and the interpretive limit attached to each (Angrist & Pischke, 2009; Imbens & Wooldridge, 2009).

Table 5: Comparison-design assumptions and diagnostics

Assumption	Diagnostic	Interpretation limit
Parallel counterfactual trends	Pre-period plots and event study	Failure to reject is not proof
Stable group definition	Product, plant and customer mix	Selection can bias estimates
Limited spillovers	Shared staff and practices	Comparison group may be exposed
Comparable timing	Adoption dates and cohort structure	Staggered adoption needs suitable methods
Dependence and precision	Clustering at appropriate operating level	Few clusters require robust inference

Table 5 specifies checks required before interpreting the interaction coefficient.

A comparison group should be selected on substantive operating similarity and exposure to common shocks, rather than on favorable estimated results. Event-study diagnostics, alternative windows and placebo deployment dates should be reported. Inference should cluster at the level at which the dashboard was rolled out, typically plant or region, because serially correlated outcomes within clusters understate conventional standard errors (Bertrand *et al.*, 2004); with few clusters, small-sample corrections such as the wild cluster bootstrap are advisable (Cameron & Miller, 2015). Differences in treatment timing, customer mix and spillover exposure, for example where customer-service staff serve both groups, may invalidate a simple two-group interpretation.

3.5. Heterogeneity Across Shipment Types

Prespecified subgroup analyses can compare export and domestic shipments, consolidated and single-unit orders, and high- and low-complexity instruction profiles. Export orders are the subgroup in which the framework predicts the largest benefit, because they add forwarder nomination, Incoterms confirmation and export documentation to the instruction set, and time lost to documents and procedures before shipment carries a measurable trade cost (Djankov *et al.*, 2010; Hummels & Schaur, 2013). Highly configured orders may show a similar pattern, since product configuration affects order errors and time to fulfillment (Forza & Salvador, 2002). Interaction estimates and subgroup sample sizes should be reported, and subgroups should be limited to those named before analysis to avoid selective reporting. The framework predicts larger benefits where instruction gaps constrain release; that prediction remains untested.

3.6. Theoretical Implications

The proposed mechanism follows the account of visibility embedded in routines (Barratt & Oke, 2007) and the relationship between visibility and internal integration (Williams *et al.*, 2013). It also offers a testable extension of information-distortion logic to inquiry and expedite workload (Lee *et al.*, 1997). The present protocol does not confirm those extensions.

Visibility includes the readiness of information needed to ship an order as well as the location of goods. Placing instruction completeness alongside order status makes this distinction operational, and it extends the quantity, quality and freshness dimensions of visibility proposed by Caridi *et al.* (2010) with a fourth, readiness: whether the information required for the next physical step is complete. Whether that design changes behavior must be measured rather than inferred from its existence.

3.7. Managerial Implications

Several lessons follow for organizations considering similar deployments in heavy-equipment or other capital-goods distribution. Customer-supplied shipping information should be treated as a tracked object with its own completeness status rather than as free text attached to the order. Dashboards should be designed around exceptions, because a view that lists every open order is consulted rarely while one that lists the orders at risk is acted upon. Lead time should be decomposed into build and wait intervals so that improvement effort is directed at the component that information can actually control, which mirrors the value-stream logic of Lean Six Sigma in separating value-adding time from waiting (Ambali, Eyetsemitan, Oyeleye, & Fadayomi, 2021).

A documented exception-review routine is part of the intervention to be evaluated (Agboada *et al.*, 2019). Inquiry and expedite logs should be established before rollout. Adoption research supports measuring usefulness and ease of use (Agyei *et al.*, 2019), structured training and feedback (Sanni *et al.*, 2020c), and continuing review of operating indicators (Arumosoye & Obriki, 2021). These factors should be measured as implementation conditions.

3.8. Limitations and Future Research

This paper specifies an evaluation protocol and reports no order-level dataset, fitted estimates or confirmed hypotheses. A future observational evaluation will remain vulnerable to confounding, nonrandom scope selection, spillovers and inconsistent event logging. Attribution to an information system also requires separation from concurrent operational activity (Sanni *et al.*, 2020a). Evidence from one firm and product category would require further replication before broad generalization.

Future work could extend the analysis in several directions. A staged rollout across regions or plants, governed by stage-gate review in the manner used for portfolio innovation (Agyei, 2021), would allow a stepped-wedge design (Hussey & Hughes, 2007) with stronger causal identification. Adding spatial analysis of shipping lanes and destination regions, drawing on GIS methods developed for asset and infrastructure planning (Dagodzo & Ahiake Patrick, 2021a), could show where in the network instruction gaps and delays cluster. Data-driven efficiency models from other resource-intensive sectors such as agriculture (Michael & Ogunsola, 2021c) also suggest that the mechanisms studied here may apply beyond manufacturing. Linking dashboard usage logs to order outcomes would make it possible to test whether orders that were viewed or acted upon in the exception views improved more than those that were not. Research could also examine the customer side of the relationship, measuring whether improved visibility affects customer planning accuracy, order-change frequency, or satisfaction. Finally,

comparative studies across capital-goods sectors such as agricultural machinery, mining equipment, and power generation would help establish how far the proposed mechanisms generalize.

4. Conclusion

The order-visibility framework makes shipping-instruction readiness a managed part of the order cycle and provides a protocol for evaluating its effect. The hypotheses remain open, and this paper reports no measured lead-time reduction or confirmed causal effect. A defensible evaluation must separate production time from post-production waiting, include eligible open orders and account for deployment timing and concurrent changes. The contribution is a transparent route from a dashboard design to a testable operational claim.

A practical deployment should assign responsibility for missing shipping instructions before a finished order reaches dispatch. Production completion, instruction readiness, carrier booking and shipment confirmation require distinct timestamps. The dashboard should show the age and owner of each unresolved exception, with a clear escalation route and a record of corrective action. Visual access alone does not establish operational improvement. Staff must use the same event definitions and update rules across plants, distributors and customer-service teams for the proposed visibility measure to describe comparable work.

Evaluation should distinguish reductions in post-production waiting from changes in production duration, demand mix or transport availability. Open orders belong in the analysis rather than disappearing because shipment has not occurred by the observation cutoff. Lead-time dispersion and the upper-tail level answer different questions and require separate reporting. Deployment timing, staffing, customer complexity and seasonal workload require an explicit assessment. The study design should avoid treating dashboard-induced exception handling as a baseline confounder when estimating the total effect of deployment. Future research should preregister the primary outcome, comparison group and analysis window, then report incomplete records and concurrent process changes. A staged rollout across comparable sites would support stronger inference than a simple before-and-after average. Operational measures should include exception resolution time, user workload and shipment accuracy alongside speed. Negative or uneven effects deserve the same attention as improvements. The framework therefore supplies a basis for an auditable evaluation of order visibility while leaving the size, reliability and transferability of any benefit to prospective evidence.

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