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Operational versus Strategic Use of Analytics in Retail: A Comparative Case Study of Walmart and Zara

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Abstract

Retail firms collect detailed sales, logistics, and customer data, yet analytics may play different roles in routine operational decisions and in less structured strategic choices. This exploratory comparative case study examines publicly documented decision episodes at Walmart and Zara and asks whether organizational design, particularly commitment timing, helps explain the difference. A structured search yielded 27 documents published between 2003 and 2025. Using a codebook grounded in Simon's (1960) programmed/non-programmed distinction and Galbraith's (1974) information-processing perspective, the study classified 11 decision episodes: six operational, four strategic, and one ambiguous. In the documents reviewed, analytics is most visible in routine decisions made within short feedback cycles, and its role in documented strategic decisions is less clear. Zara's reported in-season production commitments show how timing may make recent sales information actionable. This is a historical description rather than a claim about current practice, and the corpus does not document the timing of Walmart's assortment commitments. The cases motivate a proposition that shorter commitment lead times may increase the share of comparable decisions materially informed by relevant current-period data. The corpus, however, neither measures that outcome nor tests the proposition. It is small, curated, and documentary; the firms differ in other ways, and one researcher conducted all coding. The study therefore makes no claim about causality, prevalence, or decision quality.

Keywords: retail analytics; managerial decision-making; organizational design; commitment timing; case study

1. Introduction and Research Gap

1.1 Background

Retailing leaves a dense digital trail. Every sale, delivery, and shelf movement produces a record, and retailers have invested heavily in systems that turn these records into decision inputs (Grover et al., 2018; Ransbotham et al., 2016). The two retailers examined here take different routes. Walmart built one of the largest analytics infrastructures in retail, centered on its Data Café analytics hubs (Marr, 2017). Zara's fast-fashion model instead depends on rapid feedback from store sales into production and allocation decisions (Ghemawat & Nueno, 2003; Caro et al., 2010).

Decisions also vary in structure. Simon (1960) distinguished programmed decisions, which are routine and well structured, from non-programmed decisions, which are novel and ambiguous. Analytics may serve the two types differently: models can support, and sometimes execute, routine replenishment, whereas non,

programmed decisions still call for judgment that data cannot replace (Orjatsalo et al., 2025). Yet published research has rarely asked whether, or why, analytics operates differently across decision types.

1.2 The Research Gap

Table 1. Decision type treated in prior studies on analytics and decision outcomes

Study	Decision type treated	Comparison of types?
Ghasemaghaei et al. (2018)	General (firm-level decision performance)	No
Ghasemaghaei (2019)	General (decision quality)	No
Kowalczyk & Gerlach (2015)	Individual decisions supported by analytics	No
Franke & Hiebl (2023)	General (perceived decision quality)	No
Szukits & Móricz (2024)	General (data-driven decision-making)	No
Chen et al. (2022)	Strategic only (speed and quality)	No
Sadiku-Dushi et al. (2026)	Strategic only (AI and decision quality)	No

The author's unpublished companion review (Hussain, 2026), a systematic review of 39 studies, reached the same conclusion: none of the included studies compared operational with strategic decisions. Readers cannot inspect that manuscript, so it serves only as context. The gap claim here rests on the published sources listed in Table 1 and applies only to the studies reviewed there, not to the literature as a whole.

The gap is specific. Research links analytics capability to decision outcomes but rarely examines how organizational design—including decision authority, centralization, and commitment timing—shifts the boundary between decisions that analytics can address and those that require other inputs. The study does not claim to be the first to notice this gap; it aims instead to formulate the issue precisely enough to be tested (Section 6).

1.3 Research Questions

RQ1. How do Walmart and Zara use analytics in operational decisions, as documented in the public record?

RQ2. How do they use analytics in strategic decisions, and what other inputs do strategic decisions draw on?

RQ3. How does organizational design, particularly decision authority and commitment timing, explain the difference between the two firms?

1.4 Contribution and Scope

The study makes a conceptual and an empirical contribution. Conceptually, Proposition A holds that shorter commitment lead times may increase the share of comparable decisions for which relevant current-period data is available before commitment and materially informs the decision. Empirically, the study assembles and codes a documented comparison of two contrasting retail operating models. It is exploratory and illustrative: it documents the existence and form of analytics-supported decisions, not their prevalence or decision quality (Section 8).

2. Literature and Theoretical Framework

2.1 What the Published Evidence Agrees On

Three findings recur in the published studies, and together they define what a case study must explain rather than assume.

First, analytics does not improve decisions simply because more data are available. Data analytics competency, which covers data quality, bigness of data, analytical skills, domain knowledge, and tool sophistication, is associated with decision quality and efficiency (Ghasemaghaei et al., 2018), but the relationship operates through mediators. Big-data use affected decision quality through data quality and diagnosticity rather than data volume (Ghasemaghaei & Calic, 2019), and the effect of analytics use on decision quality ran fully through knowledge sharing (Ghasemaghaei, 2019). Franke and Hiebl (2023) add a qualification: broader data sources and a data-driven culture improved perceived decision quality only when management accountants' data analytics skills were highly developed.

Second, the mechanisms appear to be social and organizational as well as technical. In an analysis of 136 individual decisions, Kowalczyk and Gerlach (2015) found that systematic processing of analytical output contributed to decision quality, whereas heuristic processing hindered it. Trust in the analytics expert also influenced whether advice was followed. Szukits and Móricz (2024) found that top-management support and data quality help build an analytical culture, which in turn supports data-driven decision-making.

Third, the link between decision quality and broader outcomes is inconsistent across studies. Decision quality is a common outcome measure (Ghasemaghaei et al., 2018; Awan et al., 2021), but other studies examine outcomes such as operational resilience during the COVID-19 pandemic (Li et al., 2022). Better decisions do not necessarily translate into better firm performance. Neiroukh et al. (2025) found that decision speed partly explained the effect of AI capability on performance, while decision quality was not significantly related to performance. Mamakou (2026), by contrast, identified decision quality as the central mechanism linking analytics capability to firm performance.

2.2 Where the Evidence Disagrees

The disagreements matter as much as the agreements, because they show which constructs remain unsettled.

Culture. Thirathon et al. (2017) report analytic culture as the main driver of analytics-based decision-making among senior IT managers, but Khan and Fatima (2025) found no moderating effect of analytics culture on firm performance in their chain mediation model. Culture is both the most studied condition and the least consistent one.

Centralization. Szukits and Móricz (2024) found no association between centralized data use and data-driven decision-making. This null result bears on Walmart, whose model is highly centralized (Section 5.2).

Analytics capability under pressure. Chen et al. (2022) found that COVID-19 event criticality strengthened the effect of IT-business alignment on strategic decision speed and quality but weakened the effect of big-data analytics capability on strategic decision quality; event disruption showed the reverse pattern. These findings caution against treating capability effects as context-independent.

Taken together, these findings define the gap addressed here. The studies reviewed link analytics with better decisions but say less about when, for whom, or under which structural conditions the association holds. None compares decision types, and most rely on perceptual, self-reported outcomes and cross-sectional designs. What is missing is a documented account of how the same analytics capability produces different decisions across operational and strategic decision types within real firms, and of the design conditions under which the difference appears or disappears. This study addresses the gap in kind rather than scale. Instead of relying on cross-firm survey measures, it examines documented decision episodes at two retailers with contrasting operating models. It traces how commitment lead time, a design choice under management control, places decisions on one side or the other of the boundary between decisions analytics can address and those it cannot.

2.3 Classifying Decisions

This study adapts Simon's (1960) distinction into three categories, each with explicit coding rules (Table 2). Scale, financial value, and executive involvement do not by themselves make a decision strategic. A large replenishment decision may remain operational if it is routine and well structured, while a small but hard-to-reverse design choice can be strategic in content. Episodes with features of both are classified as ambiguous, and the reason is recorded. These are analytical categories for this study rather than mutually exclusive natural kinds, so mixed or changing episodes call for caution.

Data availability appears in the description of a typical operational decision but is not among the coding criteria in the third column of Table 2. Keeping it out avoids defining operational decisions in a way that would predetermine the finding that they are more often supported by analytics.

When an episode includes both the design of a decision rule and its execution, the two are coded separately. Designing the rule is a strategic, infrastructural choice; applying it repeatedly is operational. The distinction matters most for the Zara case (Section 5.3). It also has a side effect worth keeping in view: it produces paired episodes drawn from the same sources (Z05 and Z06), so the episodes are not fully independent.

Table 2. Decision classification rules

Category	Definition	Criteria used in this study
Operational	Recurrent, well structured, supported by measurable near-real-time data	Frequency; structuredness; short horizon; low reversal cost of individual instances
Strategic	Novel or non-programmed; long horizon; costly to reverse	Novelty; long horizon; reversal cost; decision authority binds the firm structurally; includes design of decision rules
Ambiguous	Shares features of both	Coded explicitly as ambiguous; the reason is recorded

2.4 Organizational Design as an Information-Processing Choice

Galbraith (1974) proposed two ways organizations can respond to uncertainty. They can increase information-processing capacity through vertical information systems and lateral relations, or they can reduce the need for processing through slack resources, self-contained tasks, and decentralized decision authority. This perspective treats the operational–strategic boundary as something organizational design can shape rather than a fixed feature of a task. Centralizing commitment shifts information-processing demands toward the center; moving commitment authority closer to the point of sale reduces them. This idea underpins Proposition A.

2.5 What These Theories Do Not Cover in Contemporary Settings

Both theories predate modern analytics, but three changes matter here. First, data latency has collapsed: Galbraith's vertical information systems required costly investment, whereas point-of-sale data can now arrive within hours or minutes (Marr, 2017). Second, Simon's distinction becomes less clear at the system level, because algorithms can execute programmed decisions and escalate only exceptions, which makes the boundary partly a matter of system design (Shrestha et al., 2019). Third, big-data capability is organizational as well as technical (Grover et al., 2018). Section 6 develops these points, and Section 7 considers their implications for managers.

3. Research Design and Case Selection

3.1 Design

This comparative exploratory case study (Yin, 2018) draws on published descriptions, corporate documents, and peer-reviewed or case-based analyses of documented decisions. Documentary evidence was used because field access was unavailable. It shows what firms publicly reported and what independent analysts recorded, but it cannot reveal internal deliberations or establish decision quality. The study is therefore illustrative: it identifies patterns and develops propositions for future testing instead of estimating effects or making population-level claims.

3.2 Unit of Analysis

The unit of analysis is the decision episode, meaning a specific documented decision or a documented recurring class of decisions. Where both design and execution are documented, they are coded separately (Section 2.3). Coding at the episode level makes operational and strategic decisions directly comparable within one design, rather than requiring a comparison of whole firms.

3.3 Case Selection

The cases were selected according to three criteria: (1) major retailers with extensive public documentation; (2) contrasting operating models, with Walmart representing a centralized, scale-driven model and Zara a short-cycle, vertically integrated one; and (3) documented analytics use in both operational and strategic contexts. The two firms were also expected to differ on the design variable of greatest interest, commitment timing. For Zara, that difference is documented: the company commits roughly half of a season's production before the season begins and defers the rest (Ghemawat & Nueno, 2003; Caro et al., 2010). For Walmart, the corpus documents acquisitions and store-network decisions at the corporate level but contains no source on when the company commits to its assortment. The comparison on commitment timing is therefore better documented for Zara than for Walmart, and this asymmetry limits the conclusions that Section 5 can support.

4. Document Corpus and Coding Procedure

4.1 Search Strategy

The general search covered Google Scholar, corporate newsrooms (corporate.walmart.com and inditex.com), and the archives of The New York Times, The Wall Street Journal, Forbes, Reuters, and trade press. It included English-language material published from January 2003 through December 2025. The INFORMS PubsOnline search was an exception, running from 2000 to 2025. Search strings paired

analytics, data, dashboard, forecasting, replenishment, and RFID with Walmart, Zara, and Inditex. Appendix A lists the source-specific terms and approximate yields. Across channels these yields total about 100 records before deduplication; they are approximate and do not represent 100 unique documents.

4.2 Inclusion and Exclusion

Documents were eligible if they described a specific decision or decision practice, rather than making only general claims, and if they carried named attribution or came from a primary corporate source. For each episode, the usual corroboration threshold was one primary source or two independent secondary sources. W01 and W02 were exceptions: each relies on a single named-author press article with direct quotations from Walmart personnel (Marr, 2017; Hays, 2004). They were retained because the articles give attributed first-hand accounts of specific practices, but they do not meet the usual two-secondary-source threshold. They are therefore treated as lower-confidence, single-source episodes rather than fully corroborated evidence. Vendor marketing and untraceable claims were excluded. For example, the frequently repeated claim that Zara's RFID program raised sales by 17% was excluded because it traced only to a blog post whose source could not be located, and it is not treated as verified here.

The source categories also need qualification. "Primary" describes where a document comes from, not whether it is neutral: Walmart's press releases and Inditex's annual report are the firms' own accounts and present their decisions favorably. The single-source exception for W01 and W02 is disclosed above and in Appendix C, and these episodes should be read more cautiously than those supported by a primary source or by independently corroborated secondary sources.

4.3 The Corpus

The corpus comprises 27 documents: 14 evidence documents (four primary corporate documents, two peer-reviewed or case-based sources, and eight press documents) and 13 theoretical or contextual sources. Of the 36 works cited, 27 are part of the structured corpus; the other nine are literature-review citations. Appendix C provides the episode-level evidence and coding, and Appendix A reports search channels and approximate yields. The search was bounded by a project limit and by apparent saturation for operational episodes. Strategic episodes were less visible in the retrieved public record, perhaps because of reporting patterns, search choices, or firms' incentives to publicize selected uses. The corpus is illustrative rather than exhaustive, and its counts do not estimate how common any practice is.

Table 3. Evidence documents by type and recency

Source type	Walmart	Zara	Total
Primary corporate documents	3 (2016a, 2016b, 2019)	1 (2025)	4
Peer-reviewed / case studies	0	2 (2003, 2010)	2
Press articles	5 (2004–2017)	3 (2014–2023)	8
Evidence documents, total	**8**	**6**	**14**
Evidence documents published since 2020	0	3	3

4.4 Coding Procedure, Reliability and Reflexivity

Each episode was coded on seven fields (Appendix B): decision level, content, analytics mechanism, organizational condition, evidence location, coding rationale, and counter-evidence. The author completed two coding passes one week apart, checked the first pass against the fixed codebook, and logged each change in an audit trail (Appendix B.4). Because one researcher conducted the coding, no independent coder or intercoder agreement statistic was available. The two-pass procedure and audit trail improve transparency but cannot replace independent reliability testing, which remains a priority for later work. The author also knew, while coding, that Zara's commitment model was expected to support Proposition A. The safeguards were to record counter-evidence for every episode, to keep the ambiguous episode ambiguous, and to retain the Jet.com episode despite its poor fit with a simple narrative (Appendix B.5).

5. Comparative Findings

5.1 Descriptive Overview

Table 4 presents the 11 coded episodes, and Table 5 summarizes them. These counts describe only the corpus. They do not represent the population of retail decisions and should not be read as prevalence estimates.

Table 4. Decision episodes (full coding in Appendix C)

Table 5. Descriptive counts (corpus, not population)

ID	Firm	Episode	Level	Analytics mechanism	Source(s)
W01	Walmart	Data Café diagnosis of sales dip	Operational	Real-time dashboards; alerts	Marr (2017); lower-confidence, single-

ID	Firm	Episode	Level	Analytics mechanism	Source(s)
					source press account (Section 4.2)
W02	Walmart	Pre-hurricane stocking (Pop-Tarts episode)	Operational	Forecasting from prior storm data	Hays (2004); lower-confidence, single-source press account (Section 4.2)
W03	Walmart	AI-managed store pilot (Intelligent Retail Lab)	Operational	Real-time inventory monitoring; automated store processes	Walmart (2019)
W04	Walmart	Closure of 269 stores worldwide	Strategic	Portfolio performance analysis (models not documented)	Walmart (2016a); Tabuchi (2016)
W05	Walmart	Acquisition of Jet.com ($3.3bn)	Strategic	Data capability as stated rationale (contested)	Walmart (2016b); Picker & Abrams (2016); Olenski (2016)
Z01	Zara	Store feedback and replenishment cycle	Operational	Twice-weekly sales data → replenishment; store-manager orders	Ghemawat & Nueno (2003); Bjork (2014); Sourcing Journal (2023)
Z02	Zara	Mid-season design/production reallocation	Ambiguous	Sales-velocity data informing in-season shifts	Caro et al. (2010); Sourcing Journal (2023)
Z03	Zara	Decision to roll out item-level RFID group-wide	Strategic	Investment decision justified by pilot results	Bjork (2014); Reuters (2023); Inditex (2025)
Z04	Zara	Daily RFID/SINT inventory management	Operational	Item-level tracking; instant replenishment	Inditex (2025); Sourcing Journal (2023)

ID	Firm	Episode	Level	Analytics mechanism	Source(s)
Z05	Zara	Design of the 50/50 production-commitment model	Strategic	Commitment-timing design (organizational rule)	Ghemawat & Nueno (2003); Caro et al. (2010)
Z06	Zara	Seasonal execution of the commitment rule	Operational	Application of a fixed allocation rule each season	Ghemawat & Nueno (2003); Caro et al. (2010)

Measure	Walmart	Total
Operational episodes	3	36
Strategic episodes	2	24
Ambiguous episodes	0	11
Episodes with named attribution or primary corporate source	5	611
Episodes documented after 2020	0	44

5.2 Walmart: Centralized Infrastructure, Two Documented Levels

5.2.1 Operational episodes

Marr (2017) describes Walmart's Data Cafés as analytics hubs that process real-time sales data, allowing analysts and managers to diagnose problems in minutes rather than weeks. In one documented case, analysts traced a small, unexplained dip in grocery sales to a pricing miscalculation in some regions. The senior statistical analyst interviewed framed the value in terms of time: cutting analysis from "two or three weeks to 20 or 30 minutes" saves Walmart "a lot of money" (Marr, 2017). The system also generates alerts when departmental metrics fall below set thresholds.

The hurricane episode (Hays, 2004) illustrates predictive analytics in replenishment. Before Hurricane Frances in 2004, Walmart's chief information officer, Linda M. Dillman, asked staff to forecast demand using data from earlier hurricanes. She described the approach as a way to "start predicting what's going to happen, instead of waiting for it to happen." Strawberry Pop-Tarts sold at seven times their normal rate in the affected region. A senior executive was involved, but the decision concerned replenishment, and the seniority of the decision-maker does not make it strategic (Table 2).

The third operational episode is more recent. In 2019 Walmart opened its Intelligent Retail Lab, a store in which AI systems monitor inventory and automate store processes in real time (Walmart, 2019). W03 operates at store level, but it is a single pilot rather than a chain-wide system; at scale, Walmart's operational analytics remains concentrated in its centralized hubs.

5.2.2 Strategic episodes

In January 2016, Walmart announced that it would close 269 stores worldwide, citing financial performance and fit with its broader strategy (Walmart, 2016a; Tabuchi, 2016). The public record documents the decision and its stated rationale but does not show whether analytics models informed it. In August of the same year, Walmart acquired Jet.com for approximately $3.3 billion (the Picker and Abrams headline gives $3 billion), citing technology, talent, and faster e-commerce growth (Walmart, 2016b; Picker & Abrams, 2016). A Forbes commentator argued that the deal was better explained by Walmart's data ambitions than by revenue (Olenski, 2016). This is the only documented Walmart episode in which analytics is publicly described as central to a strategic decision, and that interpretation comes from a commentator rather than from the decision-makers themselves.

5.2.3 Reading the Walmart case

The documented pattern is a heavily centralized analytics infrastructure serving operational decisions, alongside strategic decisions justified in the language of strategy and growth, with the role of analytics documented only indirectly and through secondary claims. This does not establish that analytics played no strategic role. It means only that the available public record does not reveal what role it played, a limitation that must remain explicit in the conclusions.

5.3 Zara: Short Cycles and a Designed Boundary

Zara's case requires the design-versus-execution distinction from Section 2.3, because its most important strategic decision is the design of a rule whose execution is operational.

5.3.1 Operational episodes

Store managers send sales observations to headquarters roughly twice a week, and replenishment draws on this short-cycle information (Ghemawat & Nueno, 2003). The current system is more granular than the historical one. Inditex combines prior sales, current stock availability, and daily orders from store managers to allocate stock across its network, and it has trialed increasing deliveries from two to four per week in selected Madrid stores (Sourcing Journal, 2023). With item-level RFID, each sale triggers an instant order to the stockroom for an identical replacement item (Bjork, 2014). Inditex's 2024 annual report states that

RFID and its integrated stock management system (SINT) have "unified the stock management of all our brands," allowing staff to "quickly locate any garment, wherever it is" (Inditex, 2025). These are programmed, recurring processes carried out at store level.

The execution of the commitment rule (episode Z06) is also operational: once the allocation rule has been set, applying it each season is a programmed, repeatable task.

5.3.2 Strategic episodes

Two episodes are strategic decisions that determine what the operational analytics can do. The first is the design of the 50/50 production-commitment model (episode Z05). Zara commits roughly half of a season's production before the season begins and holds the remainder for in-season decisions (Ghemawat & Nueno, 2003); Caro et al. (2010) analyze this planning design. It is a novel, long-horizon infrastructural choice, strategic in content, and it establishes Zara's short commitment lead times. The second is the RFID rollout (episode Z03), a major capital commitment described in 2014 as expanding after pilot results (Bjork, 2014) and reported as complete in the 2024 annual report (Inditex, 2025). Recent reporting conveys the scale of the investment: Inditex is replacing hard anti-theft tags with chips sewn into garments, cutting checkout times by up to 50%, as part of a €1.6 billion investment program that includes automation at Spanish distribution centers and roughly 30 new Zara store projects in the United States (Reuters, 2023).

5.3.3 The ambiguous episode

Mid-season design and production reallocation (episode Z02) involves shifting production toward models that sell and away from those that do not. These decisions recur, which is characteristic of operational decisions, but each also involves partly novel judgment about trends and design, which is characteristic of non-programmed decisions (Caro et al., 2010; Sourcing Journal, 2023). The episode is deliberately kept as the corpus's single ambiguous case, because forcing it into either category would have made the comparison tidier and less credible. It also carries the seed of a counter-reading: a recurring decision that contains novel judgment each time complicates any clean operational/strategic dichotomy (Section 6.2).

5.4 Cross-Case Comparison

Table 6. Walmart–Zara comparison across the documented corpus

Dimension	Walmart	Zara
Analytics infrastructure	Centralized analytics hubs (Data Cafés); real-time sales data	Integrated supply chain; RFID/SINT across all brands
Dominant documented mechanism	Real-time dashboards; predictive forecasting	Short feedback cycles; item-level tracking
Documented strategic use	Corporate deals; analytics role not documented or secondary	Decisions about the analytics system itself (commitment rule; RFID rollout)
Store-level role	Dashboard consumers; AI pilots, not chain-wide	Order authority plus in-store data
Commitment timing	Corporate-level for acquisitions and store network; timing of assortment commitments not documented in the corpus	Deliberately late commitments (50/50 model)
Data on allocation	Central; alerts pushed to departments	Store-manager orders combined with central stock data (Sourcing Journal, 2023)

The cross-case evidence addresses the research questions in different ways. For RQ1, both firms show substantial operational analytics: Walmart uses centralized hubs for dashboards, alerts, and forecasting, while Zara relies on short store-to-headquarters cycles and item-level tracking. For RQ2, the documented strategic decisions rarely show analytics as an input. Walmart's stated grounds for the store closures were financial performance and strategic fit (W04), and the Jet.com rationale emphasized technology, talent, and e-commerce growth (W05). Zara's RFID rollout (Z03) is described as following pilot results, and its commitment model (Z05) as an organizational design choice. None of the sources shows a model or dashboard driving these strategic decisions, although firms may not disclose their full decision processes.

RQ3 is harder to answer. The public record documents operational analytics at both firms but shows different organizational arrangements: Walmart's centralized analytics hubs and Zara's store-level information flows and integrated allocation system. Zara's documented strategic episodes concern the operating and information systems themselves, whereas analytics' role in Walmart's corporate decisions is either unreported or appears only in secondary commentary. The ambiguous assortment episode is consistent with the possibility that commitment timing affects when recent sales data can inform a decision. These comparisons are descriptive and do not isolate commitment timing from the other differences between the firms.

The strategic episodes are not directly comparable. Zara's two episodes concern its production model and inventory-tracking technology, the infrastructure that supports operational analytics. Walmart's concern a store-closure program and an acquisition. Part of the apparent difference in how closely strategy and analytics are linked may therefore reflect which decisions each firm's record happens to cover. The corpus contains no Walmart decision about its analytics infrastructure to set beside Zara's. The same limitation applies to the centralization finding of Szukits and Móricz (2024) discussed in Section 2.2: this case cannot test that finding and can only show that centralized analytics and centralized strategic commitment coexist at Walmart.

Alternative explanations. Commitment timing is only one possible explanation for the differences between the firms. Zara's vertically integrated supply chain may speed the movement from information to action; store managers' authority may affect how information is used; apparel assortment decisions may differ from Walmart's broader retail and corporate decisions; and public reporting may describe some analytics applications while omitting others. The corpus cannot distinguish among these explanations. A stronger test would compare product categories within one firm, measure lead times and decision rights directly, and account for supply-chain integration and decision type.

5.5 Counter-Evidence and the Missing Failed Implementation

The curated public corpus contains no documented failed analytics implementation. This does not mean that failures did not occur. Firms may be more likely to publicize successes, the search terms and available sources may favor visible or successful applications, and survivorship or publication bias may make failures harder to find. The study therefore claims only that these sources document certain analytics-supported decisions, not how prevalent, successful, or high-quality analytics use is. Selective reporting may also help explain why routine uses are better documented than strategic ones. Future searches should deliberately look for discontinued programs, cases in which dashboards were ignored or misleading, and reported implementation setbacks.

5.6 Connecting Proposition A to the Evidence

Proposition A (Section 6.2) distinguishes the explanatory condition from the outcome. Commitment lead time (L) is the interval between the point at which a production or order volume must be committed and the point of sale. The proposed outcome is the data-addressability rate (D): the proportion of comparable decision episodes in which relevant current-period data was available before commitment and materially informed the decision. Table 7 provides document-derived indicators of timing and allocation but does not measure D. Because the corpus does not systematically measure L or D for either firm, it cannot test the proposition.

Table 7. Documented timing and allocation characteristics, assembled from public sources

Decision class	Documented lead time (L)	Documented in-season / store-level share	Documented analytics role
Zara: replenishment	Days (twice-weekly cycle; 4×/week trial)	Store-level ordering documented	Automation-level support (Bjork, 2014; Sourcing Journal, 2023)
Zara: in-season reallocation	Weeks within season (Caro et al., 2010)	≈ half of seasonal volume available in-season (Ghemawat & Nueno, 2003)	Sales-velocity data informs shifts (Z02)
Zara: pre-season commitments	Months before season	≈ half committed pre-season (Ghemawat & Nueno, 2003)	Forecasts plus judgment; less documented
Walmart: replenishment and diagnosis	Not documented as commitment lead time; Marr (2017) reports diagnostic turnaround of minutes rather than weeks	Not documented; alerts pushed to departments	Dashboards, alerts, forecasting (W01, W02)
Walmart: store technology pilot	Pilot-to-rollout horizon, unspecified	Store-level pilot only	AI monitoring (Walmart, 2019)
Walmart: acquisitions and portfolio	Quarters to years	Centrally committed; no in-season share	Not documented (W04); secondary claims only (W05)

Table 7 offers context for Proposition A rather than a test of it. In this corpus, short-cycle decisions are more explicitly linked to analytics, while analytics' role in longer-horizon decisions is less direct or less visible. The lead times are approximate rather than firm-supplied, and the roughly 50% in-season share refers to Zara's historical design and should not be assumed to describe current practice. The corpus contains no comparable measure of Walmart's assortment commitment timing or in-season SKU-order share; its acquisitions and store-network decisions are not equivalent measures. Neither firm's data-addressability rate (D) is measured. The cases therefore motivate Proposition A but cannot establish that commitment timing produced the observed pattern.

6. Proposition Development

6.1 The Conceptual Model

The two cases can be drawn into a model (Figure 1). Organizational design choices (decision authority, commitment timing, IT architecture) determine information access and decision rights. These in turn determine commitment lead time and the degree of programmability, which shape the role analytics can play, and the observable result is the boundary between operational and strategic analytics use. Boundary conditions (data latency, reversibility, local authority, supply-chain integration) shape every arrow, and the observed boundary feeds back into later design choices. Zara's documented strategy language, "We don't want to be fast; we want to be agile and flexible" (Marta Ortega, writing in Inditex's 2022 annual report, as reported by Reuters, 2023), is itself a design statement about this boundary.

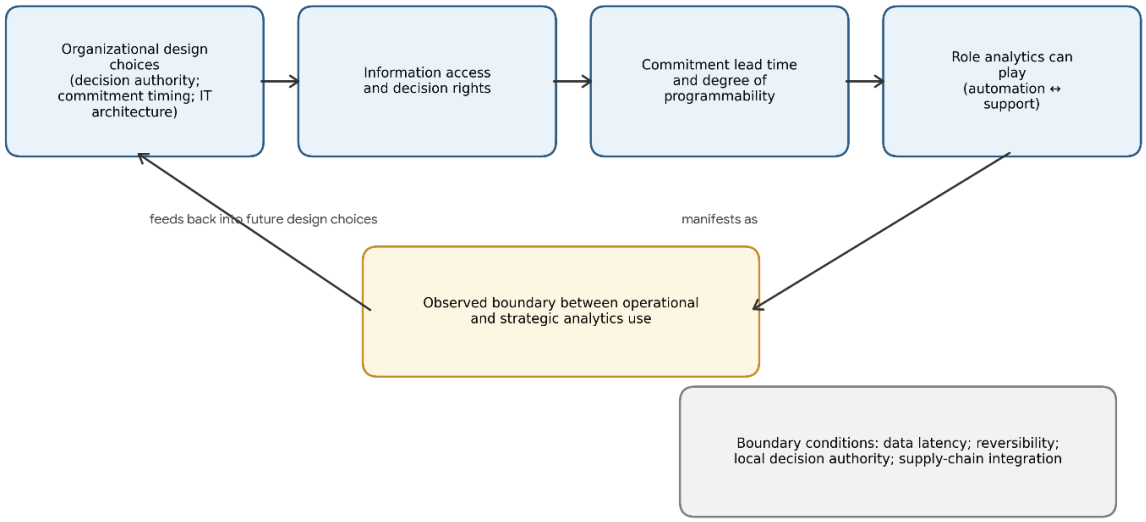


Figure 1

6.2 Proposition A

Definitions. L denotes commitment lead time: the number of days between the point at which a production or order volume must be committed and the point of sale. D denotes the data-addressability rate: the proportion of comparable decision episodes in which analytics is documented as materially informing the decision, using relevant current-period data available before commitment. Coding D requires evidence of both data availability and actual use; it cannot be inferred from commitment timing alone. The in-season/store-level share in Table 7 is a separate design indicator, not the outcome variable.

P-A. Among otherwise comparable decision classes, shorter commitment lead times (L) are associated with a higher data-addressability rate (D): a greater share of decisions can be informed by relevant current-period data available before commitment (Simon, 1960; Galbraith, 1974).

Mechanism. Data-addressability depends on whether relevant observations are available before a decision becomes binding and whether decision-makers can use them. With long lead times, relevant sales outcomes may not yet exist, leaving forecasts and judgment to carry more weight. Shorter lead times may allow recent sales data for comparable items to inform the decision before commitment. This mechanism is proposed rather than established by the present corpus. A shorter lead time does not by itself show that analytics was used, and current data may be available without displacing judgment.

Boundary conditions. The relationship should be stronger when data latency is low, individual decisions are reversible or made in small batches, local decision authority exists, and supply-chain integration is high. It should be weaker when commitments are few and difficult to reverse, or when the data do not cover the variables needed for the decision.

Testable implications. Across firms, comparable decision classes with shorter average commitment lead times should show a higher D, provided data quality, data latency, decision authority, and product characteristics are measured or controlled. Within a firm, categories with shorter lead times should show a higher D than comparable categories with longer lead times. To avoid building the expected relationship into the measure, researchers should code data availability and actual decision use independently of L.
Falsification. The proposition would be weakened or disconfirmed if comparable decision classes with shorter L do not have a higher D, or if shortening L within a firm does not increase D when relevant alternative conditions are held reasonably constant.

Status. The proposition is offered for future testing; neither the cases nor published data establish it statistically. Episode Z02 also shows that a recurring decision can involve novel judgment each time. This makes the operational–strategic boundary less binary at the margin, which is consistent with the proposed mechanism but limits how sharply any single test can separate the classes.

6.3 Proposition B

Kowalczyk and Gerlach (2015) found that systematic processing of analytical information contributed to decision quality, while heuristic processing hindered it; trust in the analytics expert also mattered for whether advice was followed. Proposition B extends this distinction to decision level. It is derived from the literature rather than the case corpus: the cases contain no evidence on urgency or processing modes and therefore neither support nor weaken it.

P-B. The effect of urgency on decision quality differs by decision level. At the operational level, urgency is absorbed in advance: programmed routines embed systematic processing in the system, so urgent

operational decisions still benefit from analytics. At the strategic level, urgency arises at the point of decision and promotes heuristic processing, which weakens analytics' relative contribution (extending Kowalczyk & Gerlach, 2015; Simon, 1960).

Boundary conditions. Time pressure at the moment of decision; the degree to which analytical output is pre-processed into recommendations rather than raw data; and trust in the analytics expert.

Status. Proposed for future testing.

7. Practical and Ethical Implications

7.1 For Retail Managers

The cases raise four questions for managers. They are prompts for diagnosis, not prescriptions supported by tested results.

1. **Which decisions are data-addressable?** Ask whether relevant data is available when the decision must be made and whether the decision recurs and can be reversed. Commitment timing is one possible design lever, but data quality, decision authority, and supply-chain integration may also constrain the use of analytics.
2. **Where should automation stop?** Recurrent, structured, and reversible decisions may be candidates for decision support or automation, provided the systems are validated and exceptions are handled appropriately. Novel or difficult-to-reverse choices should treat analytics as one input alongside judgment and other evidence.
3. **Do decision rights match information access?** Consider whether those who can act on a decision can also access and interpret the relevant data. The cases illustrate contrasting arrangements but do not establish that centralization or decentralization is universally better.
4. **How are exceptions escalated?** Where routine steps are automated, specify how unusual cases are identified, escalated, reviewed, and corrected, and who remains accountable for the final decision.

7.2 Ethical Dimensions

Three concerns fall within scope. They come from general reasoning about these systems, since the corpus offers no evidence on them, and they are flagged here rather than resolved.

Privacy. Both models depend on detailed purchase and movement records, and shoppers are not documented participants in these decisions.

Fairness. Algorithmic pricing and assortment optimization can produce different outcomes for different customer groups without any intent to discriminate.

Work design. Automated replenishment and scheduling remove discretion from the staff who carry them out, which raises questions about surveillance and job quality. Walmart's Intelligent Retail Lab, for example, monitors store activity with AI (Walmart, 2019).

The evidence assembled here cannot establish whether these systems improve or worsen outcomes. Still, because the managerial implications include selective automation, the associated risks should be acknowledged, and future research could examine them directly (Grover et al., 2018; Ransbotham et al., 2016).

8. Limitations and Future Research

This study relies on curated public documents. Firms may choose to publicize successes, journalists select stories for newsworthiness, and internal deliberations are not visible; even primary corporate documents reflect the firms' own accounts. The episodes therefore establish examples of documented practice, not its prevalence or decision quality. The corpus is modest (27 documents and 11 episodes), its search yields are approximate, and the search was bounded. The findings should be read as illustrative rather than comprehensive.

The comparison has several specific limits. Commitment timing, the main variable of interest, is documented for Zara but not for Walmart's assortment decisions. The strategic episodes are also mismatched: Zara's concern its operating and information systems, while Walmart's concern store closures and an acquisition. Some episodes share sources (Z05 with Z06, Z03 with Z04), so these 11 episodes are not 11 independent observations. The firms also differ in vertical integration, product category, store-level authority, and scale, so the study cannot isolate commitment timing as the cause of the observed pattern.
One researcher, who knew the expected result, coded the episodes. The two-pass procedure and audit trail improve transparency but cannot substitute for an independent reliability check, which was not possible for this study. Two Walmart episodes also each rely on a single press article (Section 4.2). Finally, the corpus includes no documented failed implementation. Survivorship and publication bias therefore remain likely, and routine analytics uses may also be more visible because they are reported more often than strategic uses (Section 5.5).

Future research could use interview-based cases with independent coding to observe decision processes directly, deliberately sample failed implementations, and measure commitment lead times, decision authority, data latency, and the data-addressability rate using rules independent of lead time. It should record in-season commitment shares separately as an organizational-design indicator, include Walmart

decisions about its own analytics infrastructure to make the cases more comparable, and assess decision outcomes with measures independent of self-report.

9. Conclusion

The cases suggest that analytics use may depend not only on analytical capability but also on when a decision must be made, how structured it is, and who has authority over it. In the public documents reviewed, analytics is more visible in routine, short-cycle decisions than in strategic corporate decisions. Zara's reported production-commitment model offers one possible explanation: it may allow recent sales information to inform some decisions before commitments are fixed. The public record, however, documents commitment timing for only one firm and may shape which uses of analytics are visible. These cases cannot show that timing caused the contrast; the sample is small, the measures are approximate, and the firms differ in other important ways. Proposition A should therefore be treated as a hypothesis for future testing rather than a finding. Testing it will require comparable data within or across firms, independent coding, measured lead times, and attention to unsuccessful implementations and decision outcomes.

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Appendix A. Search Strategy

Database / source	Search strings (variants)	Period	Yield
Google Scholar	("Walmart" OR "Zara" OR Inditex) AND (analytics OR data OR dashboard OR RFID OR forecasting OR replenishment)	2003–2025	~60 records screened at title/snippet
INFORMS PubsOnline	"fast fashion" AND (decision OR production planning); "Zara"	2000–2025	12 records
NYT / WSJ / Forbes / Reuters archives	Walmart data café; Walmart Jet.com; Zara RFID; Walmart hurricane Pop-Tarts; Inditex technology investment	2004–2023	22 articles
Corporate newsrooms	Walmart press releases 2016, 2019; Inditex annual reports	2016–2025	6 documents

Inclusion criteria: specific episodes; named attribution or primary corporate documents; normally one primary source or two independent secondary sources per episode. Exception: W01 and W02 each rely on one named-author press article with direct quotations from Walmart personnel; both are retained as lower-confidence, single-source episodes and are identified as such in Section 4.2 and Appendix C. Exclusions: untraceable figures (notably the 17% RFID sales claim, whose only source was a blog post), vendor marketing, and unattributed content. Stopping rule: a fixed project limit plus saturation for operational episodes. Strategic episodes were scarce in the public record, which is reported here as a finding rather than concealed.

Appendix B. Coding Manual, Reliability and Reflexivity

B.1–B.3 Code definitions

Level: operational / strategic / ambiguous, per Table 2. A rule and its execution are coded as separate episodes where both are documented.

Mechanism: forecasting; real-time diagnosis; item-level tracking; portfolio analysis; design choice; none documented.

Organizational condition: centralization or decentralization of authority; commitment timing; supply-chain integration; presence of a corporate investment decision.

B.4 Reliability procedure

One coder; two passes separated by one week; an audit trail of coding changes (four changes between passes, all at the ambiguous/strategic level). No independent intercoder agreement statistic was possible, and none is claimed.

B.5 Reflexivity statement

The author knew during coding that Zara's commitment model was expected to support Proposition A. Two safeguards were used: the counter-evidence rule (every episode had to record what complicates its classification) and the deliberate retention of the ambiguous episode Z02 as ambiguous, instead of resolving it in favor of the preferred reading. Episode W05 (Jet.com) was retained even though it does not fit the narrative cleanly.

Appendix C. Full Coding Table

Doc ID	Firm	Source (type, year)	Decision episode	Level	Mechanism	Organizational condition	Evidence (location)	Coding rationale	Counter-evidence
W01	Walmart	Forbes (T2), 2017	Data Café diagnosis of sales dip	Operational	Real-time dashboards; automated alerts	Centralized analytics hub; teams bring problems to the Café	Marr (2017), article body; Peddamail quotes	Routine, structured, near-real-time corrective action	Some reporting ran on weekly/monthly cadence; latency not always minutes. Single press source (Section 4.2)
W02	Walmart	NYT (T2), 2004	Pre-hurricane stocking	Operational	Forecasting from prior storm data	Central merchandising; CIO-led demand prediction	Hays (2004), article body; Dillman quotes	Replenishment decision; short horizon; repeatable pattern	Executed by a senior executive; seniority alone does not make it strategic (Table 2). Single press source (Section 4.2)
W03	Walmart	Press release	Intelligent	Operational	Real-time	Store-level	Walmart	Routine,	Pilot, not chain-

Doc ID	Firm	Source (type, year)	Decision episode	Level	Mechanism	Organizational condition	Evidence (location)	Coding rationale	Counter-evidence
		(T1), 2019	Retail Lab AI store pilot		inventory monitoring; automated store processes	pilot within a controlled design	(2019), full release	structured, store-level automation	wide; outcome metrics not published
W04	Walmart	Press release (T1) + NYT (T2), 2016	Closure of 269 stores worldwide	Strategic	Portfolio performance analysis (models not documented)	Corporate-level decision	Walmart (2016a); Tabuchi (2016)	Irreversible, novel, long-horizon	Analytics role not documented; rationale cited is performance and strategy fit
W05	Walmart	Press release (T1) + NYT + Forbes (T2), 2016	Acquisition of Jet.com ($3.3bn)	Strategic	Data capability as stated rationale (contested)	Corporate acquisition decision	Walmart (2016b); Picker & Abrams (2016); Olenski (2016)	Novel, irreversible; authority at corporate level	Data rationale attributed to a commentator, not the decision-makers
Z01	Zara	HBS case (T1) +	Store-manager	Operational	Twice-weekly sales	Store managers hold	Ghemawat & Nueno	Programmed replenis	Includes some judgment

Doc ID	Firm	Source (type, year)	Decision episode	Level	Mechanism	Organizational condition	Evidence (location)	Coding rationale	Counter-evidence
		WSJ (T2), 2003/2014	feedback and replenishment cycle		data; store-manager orders	order authority; central integration	(2003); Bjork (2014)	hment on a frequent cycle	on assortment presentation
Z02	Zara	Peer-reviewed (T1) + trade press (T2), 2010/2023	Mid-season design/ production reallocation	Ambiguous	Sales-velocity data informing in-season shifts	Late-commitment structure enables reallocation	Caro et al. (2010); Sourcing Journal (2023)	Recurring but partly novel: repeats often, yet each instance needs trend judgment	Could be seen as programmed once rules exist; kept ambiguous deliberately
Z03	Zara	WSJ + Reuters + Annual report (T1/T2), 2014/2023/2025	Decision to roll out item-level RFID group-wide	Strategic	Investment decision based on pilot results	Corporate investment; phased rollout to all brands	Bjork (2014); Reuters (2023); Inditex (2025)	Novel, capital-intensive, irreversible at scale	Benefits are partly operational, but the commitment decision is strategic

Doc ID	Firm	Source (type, year)	Decision episode	Level	Mechanism	Organizational condition	Evidence (location)	Coding rationale	Counter-evidence
Z04	Zara	Annual report (T1) + trade press (T2), 2025/2023	Daily RFID/SINT inventory management	Operational	Item-level tracking; instant replenishment prompts	RFID + SINT unify stock management across brands	Inditex (2025); Sourcing Journal (2023)	Daily, programmed, automated	None significant
Z05	Zara	HBS case (T1) + peer-reviewed (T1), 2003/2010	Design of the 50/50 production-commitment model	Strategic	Commitment-timing design (organizational rule)	Deliberate organizational design choice; late commitment preserved	Ghemawat & Nueno (2003); Caro et al. (2010)	Infrastructural, novel, long-horizon; creates the conditions other episodes operate in	Design-vs-execution distinction documented: see Z06
Z06	Zara	HBS case (T1) + peer-reviewed (T1), 2003/2010	Seasonal execution of the commitment rule	Operational	Application of a fixed allocation rule each season	Rule set at corporate level; executed per season	Ghemawat & Nueno (2003); Caro et al. (2010)	Once designed, execution is programmed and	Individual seasons still require quantity judgments within the rule

Doc ID	Firm	Source (type, year)	Decision episode	Level	Mechanism	Organizational condition	Evidence (location)	Coding rationale	Counter-evidence
								repeatable	