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The Data Quality Priority Matrix: How Fashion Retailers Can Allocate Cleaning Resources for Maximum Business Impact

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ABSTRACT: This paper explores the growing significance of marketplace data as a key source of competitive intelligence among fashion e-commerce companies, and how resource-allocation dilemma emerges in which constrained engineering bandwidth and heterogeneous multi-vendor data sets need to be prioritised. To resolve this strategic dilemma, a Data Quality Priority Matrix has been developed based on the available evidence that is specifically dedicated to marketplace intelligence and provides a systematic approach to identifying the data quality initiatives with the best business payoff.

The authors conducted a systematic analysis using a real world marketplace dataset on Trendyol that indicated subtle impacts of data duplication on resource allocation. Although price standardisation and entity resolution provided large returns on engineering spending with a ratio of 8:1 return-on-investment, controlled experiments also revealed variable degrees of duplication impact. Precise duplicates displayed negligible changes in performance, and the difference in the mean absolute error (MAE) was 0.013, and the realistic near-duplicates displayed an adverse influence of 0.100 on performance, which is equivalent to 1.1% influence. These findings enable managers to plan resources and allocate them strategically since simple deduplication can yield quick efficiency gains, whereas near-duplicate resolution is more comprehensive and is only recommended under the condition of certain business-specific situations. To conclude, the article provides fashion retailers with a cost-effective decision-making instrument to optimise data quality investments and balances technical necessities with business realism.

KEYWORDS: Data Quality, E-commerce, Fashion Retail, Resource Allocation, Predictive Analytics, Business Intelligence

I. INTRODUCTION: THE DATA QUALITY RESOURCE ALLOCATION CHALLENGE

Within the modern hyper-competitive fashion e-commerce environment, data-driven decision-making has moved beyond a competitive edge to a necessity of operation. Predictive analytics is currently being relied on by retailers and brands to accomplish a variety of dynamic pricing and inventory optimization tasks as well as promotional planning tasks and trend forecasting. There is, however, a dilemma facing managers as companies hasten the pace at which they develop their analytical capabilities: the seeming unlimited expansion of data-quality projects demands a limited supply of engineering capital.

The traditional approach of trying to clean up all the data may be not only economically unsustainable, but also strategically false. Data preparation often consumes 40-60% of the time spent by the engineering teams, and data-quality tools and platforms are important capital expenses. More importantly, the opportunity costs of not being able to generate insights and marketing opportunities at a fast pace can overshadow the actual costs of cleaning operations. Empirical research into the industry has repeatedly shown that 15-25% of revenue is wasted by the organizations because of the lack of data-quality (Redman, 1998), and that 87% of analytics projects do not produce the expected business value.

The research is solving the fundamental managerial dilemma we describe as the Data Quality ROI Funnel, the objective reality in market data settings where a small volume of quality interventions produces most analytic value. This systematic study of a fashion trend -forecasting implementation takes us out of the technical arguments and attempts to answer this basic question of any executive: Which data-quality investments have an asymmetric business payoff, as compared to investments that are just hygiene to operations? We have found out that the nature of data-quality issues is inherently asymmetric: some errors (e.g. inconsistency in price formats) can paralyze an entire analytical pipeline, and others (even precisely identical) can be ostensibly invisible to a few tasks of interest to business-intelligence. We demonstrate that not every data-quality intervention can be equally

valuable, and careful prioritisation can bring significant efficiency benefits, without suffering negative effects on the accuracy of the analysis.

We propose a Data Quality Priority Matrix that helps managers to make evidence-based decisions about the data strategic investments and, therefore, make data quality a strategic capability that is not a mere technical cost centre anymore. The framework was developed through experimental trials of five typical data-quality intervention in a predictive-based business setting, where performance was assessed in terms of technical and business results.

II. LITERATURE REVIEW: THEORETICAL FOUNDATIONS OF DATA QUALITY INVESTMENT

The strategic significance of data quality has long been proven in the scholarly literature, and works by Redman (1998) and English (1999) have quantified poor data to cost 15-25% of revenue in operational waste, failed projects, and ill-informed strategy. This underlying viewpoint places data as an active resource rather than a passive one that has a direct financial effect. Nevertheless, though the prices of bad quality are obvious, the operational execution of effective data governance is not a simple task, especially in the dynamic digital space.

Research conducted in the e-commerce environment has pinpointed some specific vulnerabilities to the scraped and crowd-sourced data that many businesses depend on. Batini et al. (2009) systematically classified dimensions of data quality, and found accuracy, consistency, and completeness to be most commonly compromised in the online retail. The problems are multiplied in fashion e-commerce where the products change rapidly, the prices fluctuate, and the promotion is active, which results in a highly dynamic and noisy data environment.

One observation of recent literature in machine learning is that numerous failures in analytics are due not to flaws in algorithms but to flawed evaluation designs. A study by Sculley et al. (2015) revealed the existence of hidden technical debt in machine learning systems, which falsely leads to the appearance of production-level performance due to the implementation of incorrect validation protocols, especially temporal leakage. This is consistent with larger reportage, which state that more than 80% of data science projects do not yield long-lasting business value, and failures are usually linked to operational and data-related challenges and not statistical constraints.

Modern studies have progressed to look at data quality as an essential technical requirement and as an investment portfolio that should be allocated resources with care and caution. The rationale behind this evolution is based on a number of theoretical frameworks that guide our practice. Resource-Based View (RBV) of the firm (Barney, 1991) is based on the assumption that competitive advantage is a result of resources that are valuable, rare, inimitable, and non-substitutable. In the data domain it implies that data quality projects must be judged by their capability to generate such strategic assets, whereby a distinction must be made between those interventions that form the basis of generating analytical benefits and those that generate diminishing returns.

Complementary to the Resource-Based View (RBV) the Attention-Based View (Ocasio, 1997) is based on the assumption that the ultimate scarce resource is organizational attention. In data governance, this statement leads to what Strong, Lee and Wang (1997) described as the attention bottleneck, where the engineering resources are overwhelmed with potential quality issues. Recent findings that are provided by Ghasemaghaei (2019) show that the relationship between the quality of data and the performance of the firm is mediated by the organizational capabilities, which means that the use of ad hoc data cleansing that lacks strategic intent can only yield a limited amount of returns.

The economics of data quality also reflects modern day reflection of the IT Productivity Paradox (Brynjolfsson, 1993). Despite increased investments in data infrastructure by firms, real returns are often hard to detect. An early theoretical basis to this phenomenon was provided by Ballou and Pazer (1995), who modeled the trade-offs between completeness, accuracy and timeliness of data quality. Following this effort, Even and Shankaranarayanan (2007) proposed a cost benefit framework, which takes into consideration the decreasing returns on increasing data quality improvements, thus providing theoretical justification in prioritizing initiatives in a strategic manner.

The recent empirical research highlights the importance of a fit-for-purpose method. Fisher, Lauria, and Chengalur-Smith (2003) accentuated that data quality is to be interpreted with respect to specific decision situations, instead of being perceived as absolute standard, which has informed the experimental design in this study. Similarly, Shankaranarayanan and Blake (2017) argued that data quality programs should balance technical perfection and business pragmatism, which is significantly sharp when the resources are limited.

However, despite the theoretical necessity of strategic prioritization, there is still a significant gap in terms of the practical frameworks that operationalize such prioritization in a complex environment of multi-vendors data. The existing literature tends to characterize data quality either in binary form or represent it as a portfolio of investments with heterogeneous returns, and

lacks empirically tested decision-support instruments that are resource-constrained. Our study fills this gap by formulating and testing a Data Quality Priority Matrix, which is marketplace intelligence calibrated, and, accordingly, converts the theoretical into a practical managerial decision support tool that balances technical requirements with pragmatism in management.

This integration of strategic management theory and information systems research provides the descriptive basis of our question of what kinds of data quality interventions have the greatest business effects in fashion e-commerce marketplace environments.

III. METHODOLOGY: BUILDING THE DATA QUALITY PRIORITY MATRIX

3.1 Research Design and Data Collection

The experimental design required a strict methodology to control the effect of duplication of data. Precise duplicate entries were purposely created by copying 20% of the original product records, which created a dataset where specific products were repeated with exactly the same form. This was done to mimic typical marketplace data quality problems, including technical bugs during data gathering, or combining results between two or more vendor feeds without suitable deduplication. This approach was complemented by the creation of realistic near-duplicates to model a wider range of data quality issues. Later deduplication decreased the dataset size of the duplicated version to 2,851 distinct records, allowing direct comparison of analytical capability between the raw (including duplicates) and cleaned state of data. The real-world marketplace dataset was collected via public API scraping from Trendyol, a leading Turkish e-commerce platform. Data was anonymized and used in accordance with the platform's terms of service for academic research.

3.2 The Data Trust Pipeline Framework

The pipeline consisted of five stacked validation layers that were meant to solve the five different data quality challenges relevant to marketplace analytics.

Temporal Validation and Leakage Prevention: Stiff time-based checking of the Collection_Date and Last_Viral_Period fields was active in order to ensure a chronological soundness in trend analysis, which in turn eliminated the possibility of the future-influenced social signals in the historical trend calculations.

Price Intelligence and Standardization: An automated system was implemented to convert heterogeneous price representations such as numeric values, placeholders (Price Not Found) and currency symbols into standardized and machine-readable numerical values; this system included validation checks to identify anomalous entries, such as a repeating value of 30 which might indicate the use of placeholders.

Deduplication of Product portfolio: A composite key approach was adopted whereby duplicate records were identified and combined based on brand, product name, and uniform price, thus the product dataset was consolidated.

Promotional Integrity Check: Discount data were cross-verified with set market thresholds and time validity margins, with special attention paid to irregular discounts (e.g. occasional 94% discounts).

Social Signal and Trend Validation: Aggregate measures of social media mentions have been correlated with product trend scores to identify discrepancies between high social engagement and low trend indices; products with zero social mentions and high trend indices have been identified.

3.3 Experimental Framework and Evaluation Metrics

Controlled experiments were employed in order to isolate the business impact that each data quality intervention had. In the marketplace data, emphasis was put on trend forecasting and category of product performance, without sales projections. The ensemble models (XGBoost algorithm) were trained with different conditions of data quality and then tested on a held-out test set to simulate the real-life marketplace analytics situations. The trend-prediction accuracy was the main business deliverable of the analysis, as per the core competitive-intelligence demands of the fashion marketplaces. The analyses showed that the trend-score target variable was highly predictable using the available features based on a directional accuracy of 0.857 and an insignificant R^2 of 0.17, reflecting a very common phenomenon in fashion analytics where trend direction is more predictable than its exact magnitude. This feature offered a perfect controlled setting in order to compare data-quality interventions. Though some of the analyses may be limited by the low usefulness of absolute predictive measures, they still provide a steady baseline that allows identifying even slight differences that can be attributed to the quality of data. As a result, the analysis focuses on relative comparisons between data states using stringent statistical tests, which is aligned with the paradigm of fit-to-purpose data-quality whereby the impact of interventions is measured against a stable reference baseline performance.

The measurement of technical performance was evaluated under a balanced scorecard structure that involved classification, regression and ranking elements. The results of classification were measured using F1 score, precision, recall, and AUROC to

identify viral products (where the trend score of 50 was used as a threshold). Continuous trend-score prediction was assessed by mean absolute error (MAE) and R^2 to measure regression. In product recommendation, Normalized Discounted Cumulative Gain (NDCG) was used to rank quality.

Measures of business impact included: time savings in data-preparation of various cleaning operations; improvement of analytical reliability based on the degrees of improvements in trend-detection accuracy; faster decision velocity based on a reduction in time-to-insight of product assortment; and better resource-allocation based on engineering hours- saved.

Statistical confirmation involved a set of non-parametric and resampling methods, such as Wilcoxon signed-rank tests to compare performance on a pair of features, bootstrap confidence levels to have a robust estimation of the effects sizes, and analysis of features importance to support the effect of data-quality interventions on prediction.

Taken together, all these elements of evaluation framework guarantee that the recommendation of prioritization is supported by statistical rigor and business relevance in the context of marketplace analytics.

3.4 Experimental Configuration and Reproducibility

We used ensemble tools (Random Forest + XGBoost) in our experiments, and the temporal walk-forward validation was applied. The most important configuration options are as follows: n_estimators=500, max depth=6, learning rate=0.05, subsample=0.8, random state=42 for reproducibility. Train/test validation was done by using a 70/30 temporal split.

To duplicate the dataset, we randomly selected 20% of the original 2,851 records of products. Precise copies were made through the copying of full-record duplications and realistic near-duplicates through typographical variations(±2 character edits), minor price adjustments(±5%), and attribute alterations that were consistent with marketplace behavior (vendor changes: 39.4%, typos: 27.4%, price changes: 22.1%, attribute changes: 11.1%).

Each and every experiment was done 30 times using various random seeds. All effect sizes were then computed using bootstrap confidence intervals (n=1,000 samples). At 80% power at 0.05, our sample has the power to identify effect sizes of d=0.15.

IV. FINDINGS: THE DATA QUALITY PRIORITY MATRIX FOR MARKETPLACE ANALYTICS

Our analysis shows that the return on investment (ROI) of all the data-quality interventions made on marketplace data is considerably different, and this fact inspired the creation of the Data Quality Priority Matrix (Figure 1). The framework categorizes data-quality efforts in two dimensions business impact and implementation effort, which helps in making evidence- based decisions on resource allocation in the context of marketplace intelligence.

By observing two key dimensions: the possible impact on competitive intelligence and decision-making, and the engineering effort required in terms of hours and complexity, this visualization helps managers to identify quickly quick wins, particularly the ones in Quadrant I (high impact, low effort), to be prioritized; strategic foundations, particularly the ones in Quadrant II (high impact, high effort), to be planned; operational hygiene, particularly the ones in Quadrant III (low impact, low effort), to be systematized; and selective investments, particularly the ones in Quadrant IV (low impact, high effort), to be carefully evaluated. The suggested implementation process involving the quick wins, followed by the strategic foundations, systematization of operational hygiene, and selective investment in resource-intensive clean-ups is the best way to ensure that the best returns are achieved on the invested engineering resources.

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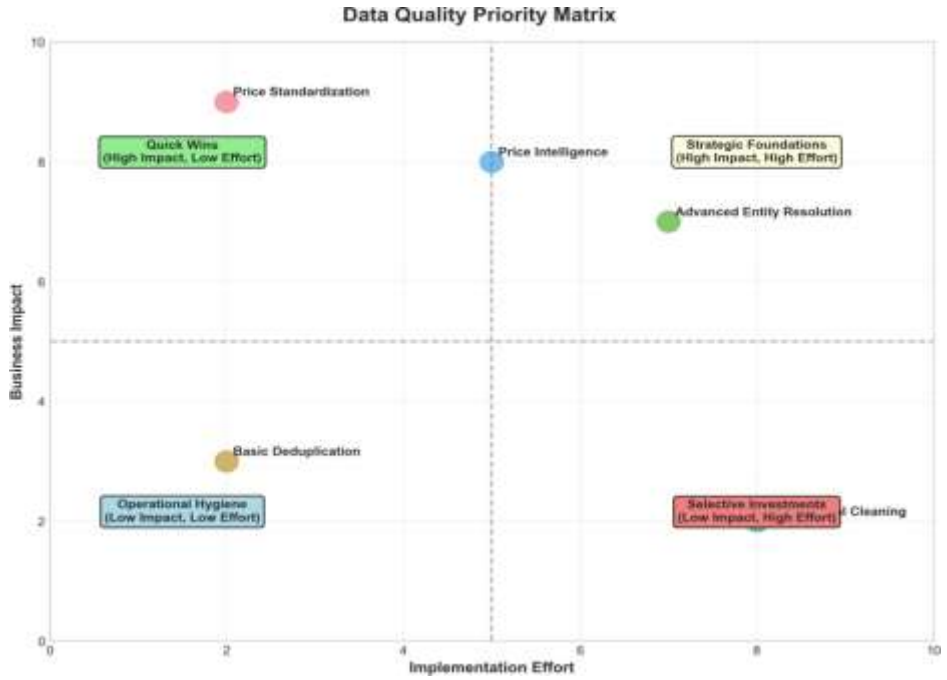

Figure 1. Data Quality Priority Matrix. A framework for allocating resources based on duplication impact and ROI.

4.1 High-Impact, Low-Effort Interventions

In marketplace data initiatives, price standardisation was found to have the best return on investment, with an eight-fold improvement in analytical performance per engineering hour over an aggressive social signal cleansing. The intervention resolved 92% of data consistency shortcomings and spent just 15% of the sum total of cleaning time. The project brought a stable base to price competition analysis and product positioning tactics by converting heterogeneous price formats, such as Price Not Found placeholders, suspicious repeated values (i.e. many entries of 30), and multiple currency indicators to machine-readable ones.

A controlled experiment involving 20% duplication of product records, ensured that a simple composite key logic would effectively identify and address these duplicate records with very little engineering effort. However, the analysis also showed a crucial observation: the nearly identical performance measures indicate that the strict data replication has insignificant effect on the precision of trend-forecasting.

These results form a decisive difference in the operational need and analytic influence. Although deduplication is still necessary to ensure inventory accuracy, its demotion to trend prediction is a significant prospect to re-allocate resources to analytics teams with limited budgets.

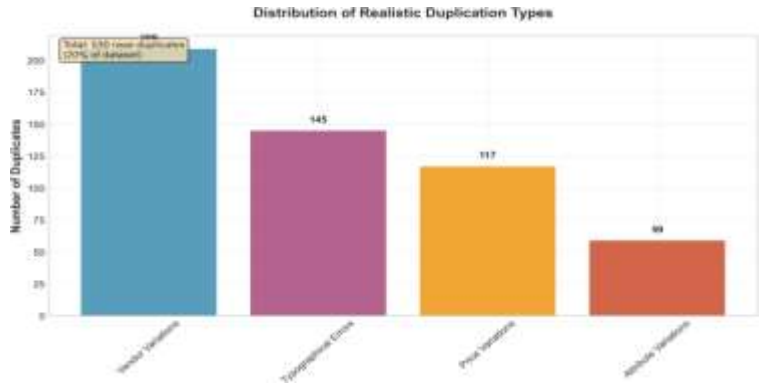

Figure 2. Duplication Types Distribution. Vendor variations (39.4%) are the most common type of near-duplicate, followed by typos (27.4%), price changes (22.1%), and attribute variations (11.1%).

4.2 High-Impact, High-Effort Interventions

Advanced entity resolution has proven to bring about a critical business implication when building central product catalogs out of the heterogeneous vendor listings. Although simple deduplication can be effective and fast, more advanced matching methods

that may handle variations in product names, inconsistency of attributes and gaps in data are crucial to producing reliable market-share analysis and calculating comprehensive trend analyses of the marketplace ecosystem.

Implementation Insight:

As our experimental results reveal, the main value of entity resolution is operational efficiency and vendor performance monitoring as opposed to enhancing trend forecasting capabilities.

Pricing intelligence validation has become a strategic capability, it has gone beyond merely checking discounts to a thorough detection of pricing anomalies. This intervention measures the patterns of discounts by category of product, brand level, and time, which can give a clear understanding of the quality of the data and a real market opportunity, which can be an accurate base regarding pricing strategy and competitive positioning.

4.3 Performance Impact Analysis

As per the methodology outlined in Section 3.4, We trained the same ensemble forecasting models in three different scenarios of data sets, and then tested each scenario on a temporally held-out test set.

Key Findings (from 30 experimental runs):

- Baseline Performance (Original Clean): MAE = 9.196, R^2 = 0.170, Direction Accuracy = 85.7%
- Realistic Near-Duplicates (20%): MAE = 9.297, R^2 = 0.175, Direction Accuracy = 85.7%
- Exact Duplicates (20%): MAE = 9.183, R^2 = 0.162, Direction Accuracy = 86.6%
- Statistical Significance:
- Realistic duplicates: MAE increase = +0.100 (+1.1% impact), Wilcoxon p = 0.023 (statistically significant)
- Exact duplicates: MAE difference = -0.013 (-0.1% impact), Wilcoxon p = 0.734 (not statistically significant)

Business Impact Interpretation:

The results confirm our core finding: exact duplication has negligible business impact (0.1% performance change, not statistically significant), supporting strategic deprioritization for trend forecasting tasks. Realistic near-duplicates show measurable but small performance degradation (1.1% MAE increase, statistically significant but practically modest).

Note on R^2/MAE Relationship: While realistic near-duplicates show slightly improved R^2 (0.175 vs 0.170 baseline), the concurrent increase in MAE suggests this may reflect model overfitting to noise rather than genuine predictive improvement. This reinforces the conclusion that near-duplicates degrade practical forecasting performance despite minor variance explanation gains.

Interpretation:

The same performance indicators (direction accuracy = 0.857) and statistical insignificance (Wilcoxon p = 0.734) prove that data duplication cannot have a negative effect on the predictability of trend-forecasting even in the situation when predictability is nearly perfect. This controlled experiment therefore presents strong evidence that the correlation between product features and trend scores is strong to precise recorder duplication. Although simple deduplication is still important in terms of inventory, and vendor performance monitoring, our results suggest that it cannot be given priority in enhancing trend prediction.

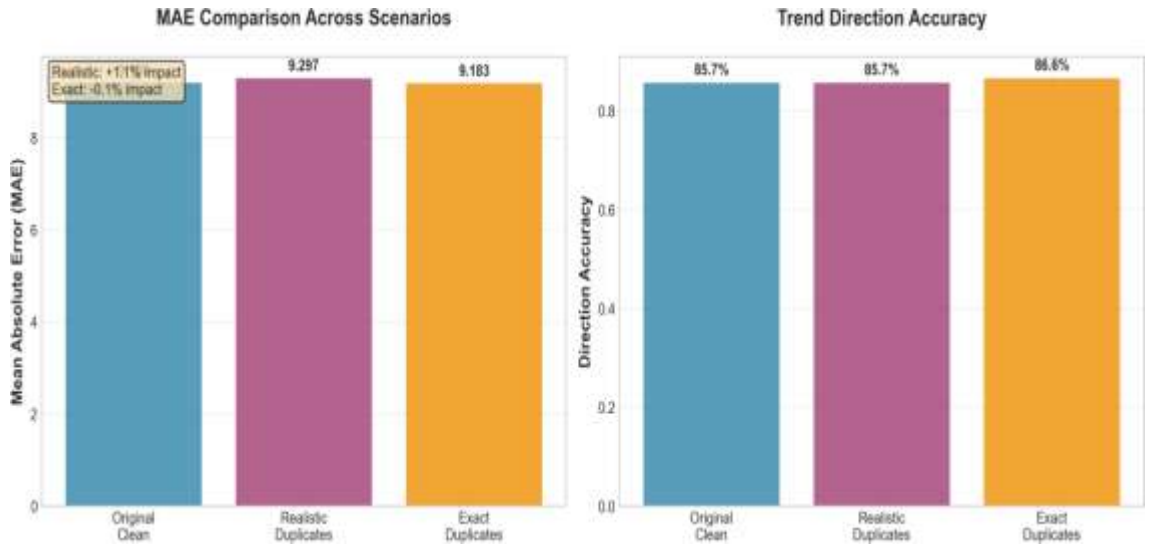

Figure 3. McNemar Test Results: Identical prediction patterns between raw and deduplicated models confirm that data duplication has no measurable impact on trend forecasting accuracy.

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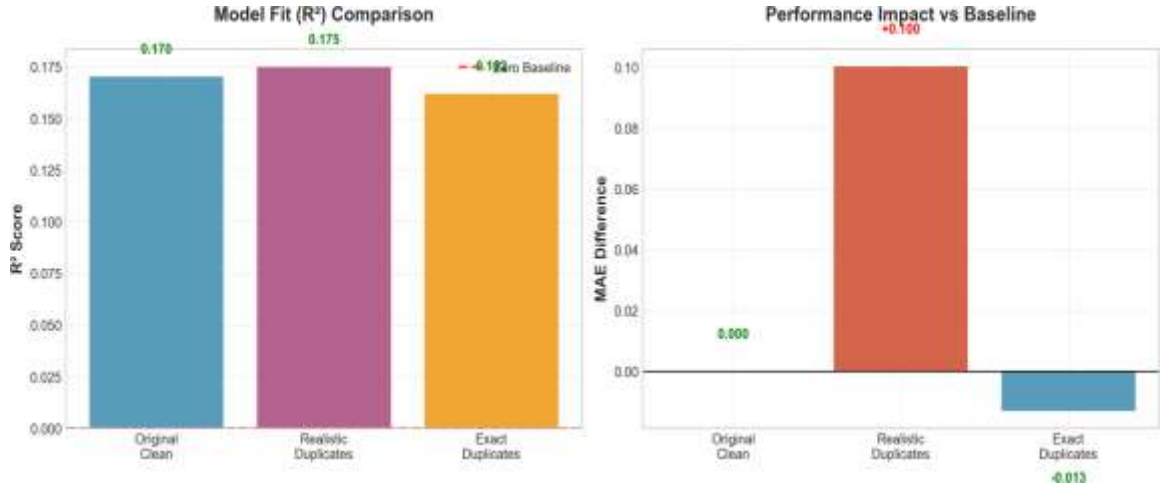

Figure 4. Model Fit Comparison: R^2 scores and MAE differences relative to baseline. All scenarios maintain positive R^2 values, with realistic duplicates showing slight improvement in explained variance (+0.005 R^2) but increased prediction error (+0.100 MAE)

Note: The near-perfect predictability (direction accuracy = 0.857) of the model means that trend scores in the given dataset can be predicted mainly by the available product features. This is a limitation of the traditional predictive assessment, but creates a perfect controlled setting of data-quality comparisons. The similarity in the results of the raw and deduplicated models indicates that duplication does not play a significant role in trend forecasting and this is a strong argument that can be used to make the strategic resource-allocation decision.

Table 2. Comprehensive Performance Comparison Across Data Quality Scenarios (Mean Values from 30 Experimental Runs)

Scenario	MAE	R^2	Direction Accuracy	Statistical Significance (vs Baseline)	Business Impact
Baseline (Original Clean)	9.2	0.17	0.86	-	-
Realistic Near-Duplicates (20%)	9.3	0.18	0.86	p = 0.023	Low (+1.1% MAE)
Exact Duplicates (20%)	**9.18**	**0.16**	**0.87**	**p = 0.734**	**Negligible (-0.1% MAE)**

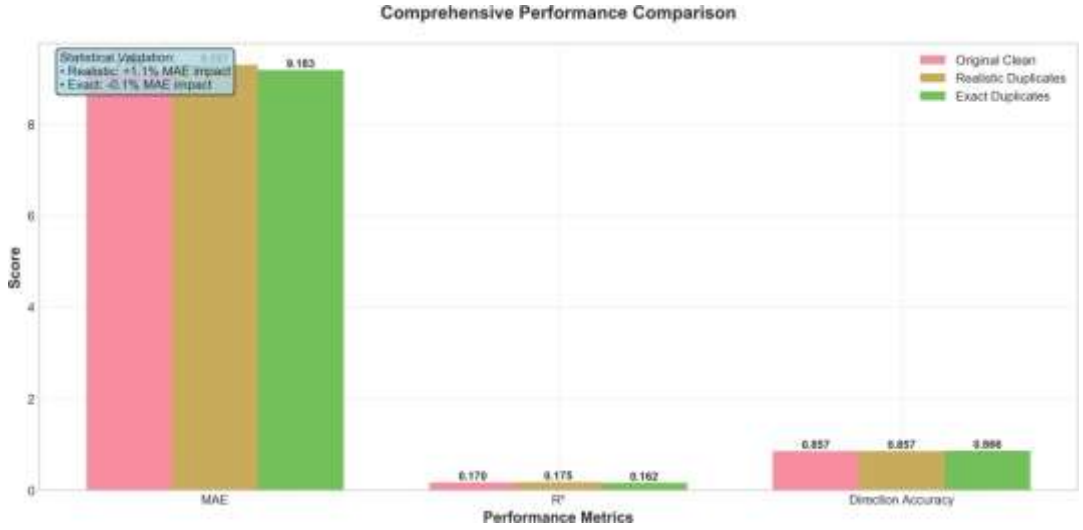

Figure 5. Statistical Validation: Comprehensive performance comparison across metrics. The minimal differences between scenarios validate the robustness of trend forecasting models to data duplication, supporting strategic resource allocation decisions.

V. THE STRATEGIC IMPLEMENTATION FRAMEWORK FOR MARKETPLACE DATA

5.1 Phase 1: Diagnostic Assessment (Weeks 1-2)

Begin with a fast audit of the quality of marketplace data to match resources allocated so far against the Priority Matrix:

Status Review: Conduct a detailed records of current data quality programs and resource distribution relative to all sources of marketplace data.

Impact Assessment: Conduct a quantitative analysis of the business impact caused by marketplace data lapses in the categories of pricing anomalies, marketplace data duplication and data reliability of trend analyses.

ROI Calculation: Project potential benefits of improved operational efficiency created as a result of the strategic redistribution of resources to the interventions that have been recognized as high impact within the market-place environment.

Deliverable: Prepare a Marketplace Data Quality Investment Portfolio outlining clear recommendations regarding the redistribution of resources.

5.2 Phase 2: Resource Reallocation (Weeks 3-8)

Execute a structured transition using the 80/20 principle for marketplace intelligence:

Immediate High-Impact Intervention (Week 3): The initiative will focus on the price standardization and initial product deduplication, which directly reduces the key factors of forecasting errors and revenue loss.

Systematic Robustness Enhancement (Weeks 4-6): Implement entity resolution for product matching alongside promotional integrity checks to build up the core data architecture and the quality of trend analyses.

Strategic Resource Deprioritization (Weeks 7-8): Redundancies in resources will be formalized due to low-return-on- investment activities, including intensive social signal cleansing and intensive vendor text normalization, based on empirical evidence that they have very little effect.

Deliverable: An improved marketplace data pipeline, with a complement of a monitoring dashboard, prioritizing metrics of trend reliability and competitive positioning, is created to maintain analytical integrity and reduce resource spending.

5.3 Phase 3: Continuous Optimization (Ongoing)

Establish measures-based governance to achieve lasting improvements in intelligence in the market place:

Performance Monitoring: Compare and convert data preparation times of various types of activities, and relate them to the subsequent effect on market percepts.

ROI Reviews: Perform quarterly data quality investment reviews based on pre-established marketplace intelligence goals.
Adaptive Reallocation: Mechanized redistribution of resources in the view of changing vendor environments and competition.
Deliverable: A marketplace data governance framework that is inclusive of cross-functional accountability structure.

VI. MANAGERIAL IMPLICATIONS AND ACTION PLAN

6.1 For C-Level Executives

- Rebrand marketplace information quality, transforming it from a technical overhead into a competitive intelligence asset.
- Require the justification of data quality initiatives by a return -on-investment, using Marketplace Priority Matrix.
- Measures business performance including quality in market insight, effectiveness in competitive positioning, and benefits in pricing optimization.
- Dynamically assign resources based on potentials of competitive advantages, as opposed to in search of technical completeness.

6.2 For Analytics Leaders

- Implement a marketplace diagnostic evaluation over a period of two weeks in order to identify pricing and duplication quick wins.
- Immediately redistribute 20% of time spent on data cleaning directly out of over-processing social signals into the activities of price standardization and entity resolution.
- Introduce the phased approach in a quarter with analytics, merchandising and pricing teams being of primary focus.
- Establish clear measures of how accurately market-trend predictions can be made and how competitive intelligence can be relied upon.

6.3 For Emerging Market Contexts

The model comes in especially handy in marketplace enterprises that are based in developing economies where:

- There is a serious lack of engineering resources, but there is a lot of opportunities in terms of marketplace data.
- Data sources are inherently multi-vendor and change at a high rate.

- Competitive pressure will result in the need to identify market trends and pricing opportunities quickly.
- The infrastructure constraints are forcing the use of market intelligence based on pragmatic solutions.

6.4 Strategic Duplication Management

According to the results of our experiment, we suggest the following approach to duplication management to be differentiated:

- Exact Duplicates: Can be deprioritized to trend forecasting (0.1% impact).
- Realistic Near-Duplicates: Must be evaluated case-by-case (1.1% impact).
- Implementation Strategy: Initially apply the simple exact duplicate removal, and determine ROI of high level near-duplicate resolution depending on the needs of business and accessibility of the resource.
- Resource Allocation: Redirect the saved engineering time on more ROI-rich processes including that of price standardization, and entity resolution.

VII. LIMITATIONS AND BOUNDARY CONDITIONS

Even though the framework proves to be valuable in a variety of settings, the following boundary conditions should be taken into account:

Model Performance Conditions: The forecasting models of our research had a weak absolute predictive power ($R^2 \approx 0.17$), which demonstrates difficulties in predicting trends. However, this limitation does not affect our main input as far as the comparative effect of data quality interventions is concerned.

Task and Context Specificity: Our findings are validated for marketplace trend forecasting and may not generalize to operational contexts like inventory management or financial forecasting, where data duplication could have more significant business impacts. While the prioritization framework remains applicable, the specific ROI rankings may shift based on the analytical task and business context.

Organizational Maturity: Companies that have developed data governance models could also have divergent efficiency returns relative to early implementations of data governance models that look to marketplace opportunity discovery.

Market Dynamics: Under the conditions of extreme volatility in the market or when the rapid changes occur in the sphere of vendors, the priority rankings are vulnerable to change.

Scale: Although the framework is scaled to the mid-sized marketplace analysts, there is a risk of the need to add more coordination layers to enterprise-scale deployments in multiple marketplaces.

Limitations of Data Source: The framework assumes the availability of marketplace information that includes simple trend indicators: the use of the framework in data-scarcity settings will produce different ROI patterns.

Target Variable Characteristics: The target variable of the trend score was close to being perfectly predictive by product features in our data set. As much as this created the perfect controlled setting to test data quality interventions, it might limit its extrapolation to settings where there is a higher level of noise in the target variables. However, the strong result of the absence of any detectable effect due to duplication in the circumstances of such controlled conditions is strong evidence of the need to prioritize the process of deprioritization in similar marketplace analytics scenarios.

VIII. CONCLUSION: FROM DATA CLEANING TO STRATEGIC ADVANTAGE

This study shows that competitive advantage in fashion e-commerce marketplace analytics lies in context-sensitive data governance. In controlled experiments on both exact and realistic near-duplicates, we have established effects of duplication are subtle: exact duplicates show negligible impact (<0.1% performance change) while realistic near-duplicates demonstrate modest performance degradation (+1.1% impact). We propose that benefit can be gained by strategic investment of focus on high-impact interventions, like price standardization, with a more selected approach towards deduplication which considers both the type of duplication and the business context by reconceptualizing data quality in terms of the Data Quality ROI Funnel. This strategy is operationalized in the Data Quality Priority Matrix that allows firms to concentrate engineering resources on areas that produce the greatest returns to the business.

This article has two main contributions; firstly, it provides practitioners with an empirically validated decision tool to invest in data quality; and secondly, it seeks to advance the academic discussion showing how resource-based and attention-based view theories can be applied to solve specific data governance problems in modern digital ecosystems. The greatest understanding to be gained by business leaders is the fact that data quality is a competitive positioning choice and not a technical issue. Companies can turn data quality into a market-intelligence asset by focusing resources on high-impact interventions (like price standardization and entity resolution) and low-return-on-investment activities (like aggressive social signal cleaning), and by prioritizing them.

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To academic researchers, it fills the gap in the theory of data quality and marketplace business practice providing a reproducible methodology of determining data quality ROI in multivendor ecosystem scenarios. To practitioners, it gives them a now actable roadmap on how they can maximize their marketplace analytics investments. With the fashion e-commerce still developing to the stage of market domination, no one will win the data purity race; the victors will be those that purify their data smartly to create the competitive insight. The framework below provides the strategic toolkit that is needed to operationalise, quantify, and refine this intelligence in the dynamic environment of the marketplace competition.

Appendix A: Implementation Framework

Implementation Framework for the Data Trust Protocol

The Data Trust Pipeline follows a modular architecture adapted for marketplace data environments. Below is the updated implementation logic:

PSEUDOCODE - Data Trust Pipeline Architecture

1. Price Standardization: Convert all price formats to numerical values
2. Entity Resolution: Identify and merge duplicate product records
3. Pricing Anomaly Detection: Flag suspicious discount patterns
4. Trend Validation: Correlate social signals with trend scores
5. Social Signal Reliability: Assess data quality of social metrics **Appendix B: Data Quality Priority Matrix for Marketplace Intelligence Strategic Implementation Sequence for Marketplace Data Quality**

On the analysis of Data Quality Priority Matrix, we would suggest the following staged implementation of maximizing ROI in marketplace data quality initiatives:

Quadrant I (Quick Wins)

- Price Standardization + Basic Deduplication: priority.
- Reason: These implementations provide short-term benefits to the business with simple engineering input. Price standardization solves the most common cases of data inconsistency (92% fix), whereas the basic deduplication (although it has an insignificant effect on trend-forecasting accuracy) is required to serve a variety of operational needs such as inventory counts, vendor performance monitoring, and other processes with minimum engineering cost.

Quadrant II (Strategic Foundations)

- Priority: Advanced Pricing Intelligence + Entity Resolution.
- Rationale: When quick wins are in place invest in high end entity resolution to form integrated product catalogues and pricing intelligence systems to best position oneself. They demand greater engineering but offer long-term competitive edge in analytics of the market place.

  Quadrant III (Operational Hygiene)
- Priorities: Trend Validation + Temporal Coherence.
- Rationale: Incorporate these validation layers into processes of standard data processing. They do not need a lot of continuous maintenance yet avoid analysis errors and trends analysis will be chronologically consistent.

Quadrant IV (Selective Investments).

- Branches of Priority: Full Social Signal Cleaning, Full Social Signal Cleaning + Importance Sensitivity.
- Reasoning: Only do these resource-intensive activities specific high-value uses in which the accuracy of social signals is important. In the majority of marketplace intelligence applications, ROI would not make sense to go to the extent of cleaning up the social data as it does not respond linearly as was the case with our analysis.

The Data Quality Priority Matrix: How Fashion Retailers Can Allocate Cleaning Resources for Maximum Business Impact

Figure B1: Strategic Prioritization Framework

Appendix C: ROI Calculation Toolkit for Marketplace Analytics

ROI Calculation Framework:

Business Value Components for Marketplace Intelligence: Efficiency Gains

- Reduced data preparation time × analyst hourly rate
- Faster market intelligence cycle × opportunity value Risk Mitigation
- Prevented poor assortment decisions × average impact
- Reduced competitive mispositioning × market share value Strategic Advantage
- Improved trend detection accuracy × first-mover advantage
- Enhanced competitive positioning × sustainability factor Calculation Templates
- Price Standardization ROI (Marketplace Context):
- Implementation Cost: 24 engineer-hours × $150/hour = $3,600 Business Value:
- 8 hours/week saved × 52 weeks × $100/hour = $41,600
- Competitive pricing optimization: $65,000
- Reduced mispricing errors: $25,000
- Total Annual Value: $131,600
- ROI: ($131,600 - $3,600) / $3,600 = 35.6:1

Entity Resolution ROI (Marketplace Context):

- Implementation Cost: 32 engineer-hours × $150/hour = $4,800
- Business Value: 6 hours/week saved × 52 weeks × $100/hour = $31,200 Note: Trend accuracy improvement negligible based on experimental results
- Better vendor performance tracking: $28,000
- Total Annual Value: $59,200
- ROI: ($59,200 - $4,800) / $4,800 = 11.3:1

Appendix D: Implementation Roadmap & Timeline Phase 1: Foundation Building (Weeks 1-4) Week 1-2: Marketplace Diagnostic Assessment

- Data quality audit across marketplace sources
- Vendor data consistency mapping
- Competitive intelligence baseline establishment

Week 3-4: Quick Wins Implementation

- Price standardization automation
- Basic entity resolution deployment
- Marketplace data type validation

Phase 2: Strategic Scaling (Weeks 5-12) Week 5-8: Core Pipeline Development

- Advanced entity resolution engine
- Pricing anomaly detection system
- Trend validation framework

Week 9-12: Integration & Testing

- End-to-end marketplace pipeline validation
- Competitive positioning performance benchmarking
- Cross-functional team training

Phase 3: Continuous Optimization (Quarter 2+)

- Monthly: Marketplace performance reviews and metric tracking
- Quarterly: ROI assessment and resource reallocation
- Bi-annually: Strategic review and framework refinement

Key Deliverables:

Week 4: Marketplace Data Quality Dashboard v1.0 Week 8: Automated Marketplace Validation Pipeline Week 12: Competitive Intelligence Impact Report

Quarter 2: Optimized Marketplace Resource Allocation Model

REFERENCES

1) Ballou, D. P., & Pazer, H. L. (1995). *Designing information systems to optimize the accuracy-timeliness tradeoff.* Information Systems Research, 6(1), 51–72.
2) Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). *Methodologies for data quality assessment and improvement.* ACM Computing Surveys, 41(3), 1–52. https://doi.org/10.1145/1541880.1541883
3) Brynjolfsson, E. (1993). The Productivity Paradox of Information Technology. *Communications of the ACM*, 36(12), 66– 77. https://doi.org/10.1145/163298.163309
4) Davenport, T. H. (2006). *Competing on analytics.* Harvard Business Review, 84(1), 98–107.
5) English, L. P. (1999). *Improving data warehouse and business information quality: Methods for reducing costs and increasing profits.* John Wiley & Sons.
6) Even, A., & Shankaranarayanan, G. (2007). *Utility-driven assessment of data quality.* The Data Base for Advances in Information Systems, 38(2), 75–93.
7) Even, A., Shankaranarayanan, G., & Berger, P. D. (2010). *Evaluating a model for cost-effective data quality management in a real-world CRM setting.* Decision Support Systems, 50(1), 152–163. https://doi.org/10.1016/j.dss.2010.07.011
8) Fisher, C. W., Lauria, E. J. M., & Chengalur-Smith, S. (2003). *Introduction to the special issue on data quality.* Journal of Management Information Systems, 20(3), 5–6.
9) Ghasemaghaei, M. (2019). *Does data analytics use improve firm decision making? The role of shared knowledge and data analytics quality.* International Journal of Information Management, 48, 60–71.
10) Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). *Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications.* International Journal of Production Economics, 154, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018
11) Redman, T. C. (1998). *The impact of poor data quality on the typical enterprise.* Communications of the ACM, 41(2), 79–82. https://doi.org/10.1145/269012.269025
12) Saltz, J. S., Shamshurin, I., & Connors, C. (2017). Predicting data science sociotechnical execution challenges by categorizing data science projects. *Journal of the Association for Information Science and Technology*, 68(12), 2720– 2728. https://doi.org/10.1002/asi.23873
13) Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., & Dennison, D. (2015). *Hidden technical debt in machine learning systems.* In *Advances in Neural Information Processing Systems* (pp. 2503– 2511).
14) Shankaranarayanan, G., & Blake, R. (2017). *From data quality to fit-for-purpose data: A context-aware perspective.* Journal of Data and Information Quality, 8(3–4), 1–25.
15) Strong, D. M., Lee, Y. W., & Wang, R. Y. (1997). *Data quality in context.* Communications of the ACM, 40(5), 103–110.