DOI: 10.71317/jgst.2.5.2026.669
Journal of Global Social Transformation
Journal homepage: https://rjsaonline.org/index.php/JGST

Digital Supply Chain Capabilities, Operational Performance and Business Performance: Regression, Diagnostics and Mediation Evidence from Fast-Fashion E-Commerce

Muhammad Affaq Khan[1], Ali Zulqarnain[2], Rabia Siddiqui[3], Nageen Tayyab[4], Muhammad Zaid Khan[5]
[1] Master in Industrial Management, University of Vaasa, Finland.
Email: x5494112@student.uwasa.fi
[2] Assistant Professor, Department of Industrial & Manufacturing Engineering, NED University of Engineering & Technology, Karachi, Pakistan.
Email: alizul@neduet.edu.pk
[3] Assistant Professor, Department of Industrial & Manufacturing Engineering, NED University of Engineering & Technology, Karachi, Pakistan.
Email: rabias@neduet.edu.pk
[4] Senior Lecturer, Department of Operations, Environment & Supply Chain Management, Institute of Business Management, Karachi, Pakistan.
Email: nageen5768t@gmail.com
[5] Lecturer, Department of Industrial & Manufacturing Engineering, NED University of Engineering & Technology, Karachi, Pakistan.
Email: muhammadzaid@neduet.edu.pk

ARTICLE INFO

Submission:
April 19, 2026
Revised:
May 03, 2026
Accepted:
May 17, 2026
Available Online:
May 30, 2026

Keywords:
Digital supply chain; demand analytics; digital inventory management; supply chain responsiveness; mediation; operational performance; business performance.

Corresponding author
Ali Zulqarnain
Email:
alizul@neduet.edu.pk

ABSTRACT

Purpose – This study examines whether demand analytics, digital inventory management and supply chain responsiveness are associated with operational performance and broader business performance, and whether operational performance mediates these relationships.

Design/methodology – The analysis uses an open respondent-level dataset of 187 owners and managers in fast-fashion e-commerce [1]. Twenty-seven Likert-type items were aggregated into five multi-item constructs. Reliability, Pearson correlations, ordinary least squares regression, heteroskedasticity-robust inference, multicollinearity and influence diagnostics, and non-parametric bootstrap mediation (5,000 resamples) were applied.

Findings – The operational-performance model was significant (R^2=0.391, F(3,183)=39.18, p<.001). The final business-performance model explained 79.8% of variance (R^2=0.798, adjusted R^2=0.794, F(4,182)=180.13, p<.001). Demand analytics (B=0.137), digital inventory management (B=0.181), supply chain responsiveness (B=0.104) and operational performance (B=0.467) were positive predictors of business performance. Variance inflation factors were low (1.61–1.80). Bootstrap indirect effects through operational performance were positive for demand analytics (0.099, 95% CI [0.038, 0.170]), digital inventory management (0.099, 95% CI [0.029, 0.173]) and supply chain responsiveness (0.049, 95% CI [0.012, 0.095]).

Practical implications – The results suggest that digital supply-chain capabilities are most useful when translated into stronger operational execution, while also retaining direct associations with business outcomes.

Originality/value – The paper separates operational and business performance, reports an explicit business-performance equation, and subjects the high explanatory power of the final model to diagnostics, robust standard errors, influence analysis and bootstrap mediation.

Introduction

Supply-chain competition is increasingly shaped by the speed with which firms can convert information into coordinated operational decisions. In digital retail, demand signals change quickly, product life cycles are short, and inventory decisions must be synchronized with customer-facing channels. These conditions make analytics, inventory visibility and responsiveness strategically important rather than merely technical functions. Contemporary supply-chain research therefore treats digital capabilities as bundles of information-processing, coordination and adaptation routines that can influence both operational outcomes and firm-level performance [2–5].

Demand analytics is one such capability. It concerns the systematic use of demand-related data to identify patterns, anticipate changes and support planning decisions. Earlier work on supply-chain analytics linked analytical capability with planning quality and operational performance [8], while subsequent research has shown that big-data analytics can generate performance benefits through dynamic capabilities, knowledge development, resilience and innovation [9,12–14,18]. Recent evidence also emphasizes that digital transformation improves supply-chain performance through integration, agility and resilience rather than through technology acquisition alone [22–25].

Digital inventory management provides the execution layer through which information is translated into stock availability, replenishment and coordination decisions. In fast-fashion e-commerce, this is particularly important because demand uncertainty and short selling windows can make excess inventory and stock-outs simultaneously costly. Digital inventory systems can improve visibility and decision speed, but their value depends on how they are integrated with demand information and responsive processes. Recent firm-level evidence indicates that digital infrastructure can reduce inventory intensity and that digitally enabled inventory control may affect financial as well as operational outcomes [27].

Supply chain responsiveness captures the ability to react rapidly and appropriately to changing customer, market and supply conditions. Responsiveness is closely related to agility and resilience, but it is analytically distinct: agility emphasizes rapid reconfiguration, resilience emphasizes resistance and recovery, while responsiveness focuses on timely adjustment to signals and requirements. Recent studies of Industry 4.0, digital transformation and supply-chain resilience consistently show that digital capabilities become valuable when they strengthen adaptive supply-chain capabilities [11,16,22–25].

A second issue is the distinction between operational performance and business performance. Operational performance concerns process-level outcomes such as reliability, speed, efficiency and execution quality, whereas business performance reflects broader organizational outcomes. Treating these concepts as interchangeable can overstate what a dataset measures. Foundational supply-chain research has explicitly distinguished operational and business performance [7], and digital supply-chain performance reviews similarly argue for multidimensional measurement [10,28]. The present study therefore models operational performance as a proximal outcome and business performance as a separate downstream outcome.

This distinction creates a theoretically meaningful mediation question. Digital supply-chain capabilities may have direct associations with business performance, but part of their contribution should materialize through better operations. A firm may possess sophisticated analytics or inventory systems, yet those capabilities create business value only when they improve execution. This logic is consistent with the resource-based view, dynamic capabilities theory and information-processing theory [2–4]. It is also consistent with recent empirical work in which resilience, innovation, knowledge development or supply-chain capabilities mediate links between digitalization and performance [14,16–18,22–24].

Against this background, the study has three objectives. First, it tests whether demand analytics (DA), digital inventory management (DIM) and supply chain responsiveness (SCR) are positively associated with operational performance (OP). Second, it estimates their direct associations with business performance (BP) while controlling for operational performance and provides a regression equation for the final business-performance model. Third, it tests whether operational performance mediates the three capability–business-performance relationships using bootstrap confidence intervals. The analysis further evaluates multicollinearity, residual behavior, heteroskedasticity and influential observations so that the high explanatory power of the business-performance model is not accepted without diagnostic scrutiny.

Literature Review and Hypothesis Development

Theoretical foundation

The resource-based view argues that sustained performance differences arise from valuable and difficult-to-replicate resources and capabilities [2]. In digital supply chains, raw technology is unlikely to satisfy this condition by itself because hardware and software can often be purchased by competitors. The more defensible source of value is the organizational capability to combine data, routines, managerial knowledge and cross-functional processes. Demand analytics, digital inventory management and responsiveness can therefore be interpreted as complementary capability bundles rather than isolated technologies.

Dynamic capabilities theory extends this argument to turbulent environments by emphasizing the capacity to sense opportunities and threats, seize them through decisions, and reconfigure resources [3]. Demand analytics primarily strengthens sensing; digital inventory management supports seizing and coordinated execution; and responsiveness reflects the ability to reconfigure or adjust operational actions. In fast-fashion e-commerce, where demand signals and product relevance can change quickly, this dynamic sequence is especially plausible.

Information-processing theory provides a third lens. Organizations facing uncertainty require greater information-processing capacity [4]. Analytics increases the ability to interpret demand signals, digital inventory systems improve the timeliness and accessibility of stock information, and responsive processes convert information into action. These theories converge on a capability-to-operation-to-business logic: digital capabilities should first improve operational execution, and stronger execution should then contribute to business outcomes.

Demand analytics and performance

Supply-chain analytics has long been associated with improved planning and operational performance [8]. The mechanism is not simply the availability of data; value arises when firms can transform data into forecasts, exception signals and actionable decisions. Big-data analytics research similarly finds that performance benefits depend on complementary dynamic capabilities and decision processes [9]. Recent studies have extended this reasoning by showing links between analytics capability and supply-chain innovation, resilience, knowledge development and performance [12–14,18].

In a fast-fashion setting, demand analytics can reduce the informational delay between market change and managerial response. Better interpretation of customer and sales signals should improve planning, resource allocation and operating consistency. It may also influence business performance directly through better assortment, pricing, timing and market responsiveness. Accordingly, the following hypotheses are proposed:

H1: Demand analytics is positively associated with operational performance.

H4: Demand analytics is positively associated with business performance.

Digital inventory management and performance

Inventory is both a service-enabling asset and a source of working-capital exposure. Digital inventory management increases the visibility and timeliness of stock information and can support more coordinated replenishment, allocation and fulfillment. Digital supply-chain performance research emphasizes that performance measurement must integrate internal process and financial perspectives [10]. More recent evidence shows that digital infrastructure can materially affect inventory holdings [27], while technology-enabled inventory control has been examined against operational and financial outcomes in retail [27].

These mechanisms are particularly relevant to e-commerce fashion because demand volatility and short product cycles amplify the costs of inaccurate inventory information. A digitally managed inventory process should improve operational performance by reducing information gaps and supporting faster decisions, while the resulting availability and efficiency can also contribute to business outcomes.

H2: Digital inventory management is positively associated with operational performance.

H5: Digital inventory management is positively associated with business performance.

Supply chain responsiveness and performance

Responsiveness concerns the ability of the supply chain to adjust to changes in demand, supply and customer requirements. It is closely connected to the broader literature on agility, resilience and adaptive capability. Industry 4.0 and digital transformation studies show that digitalization improves performance when it enhances visibility, agility, resilience and integration [11,16,22–25]. Resilience-oriented firms also achieve stronger performance through adaptive capability [16].

Responsiveness should therefore have an immediate operational benefit because faster adjustment can reduce delays, improve service and align resources with changing requirements. It can also influence business performance by improving customer outcomes and reducing the economic consequences of mismatch.

H3: Supply chain responsiveness is positively associated with operational performance.

H6: Supply chain responsiveness is positively associated with business performance.

Operational performance as a mediator

The complete set of proposed direct and mediated relationships is summarized visually in Figure 1.

Operational performance is the most proximal performance consequence of supply-chain capabilities. It reflects whether information and digital processes actually improve execution. Earlier integration research found relationships with both operational and business performance [7], while recent digitalization studies frequently identify mediating capabilities between technology and higher-level performance [14,17,18,22,23]. This suggests that operational performance can serve as a transmission mechanism from digital supply-chain capability to business outcomes.

Partial rather than full mediation is theoretically plausible. Demand analytics, inventory digitalization and responsiveness may affect business performance through operational execution, but they may also create direct commercial, strategic or decision-quality benefits.

H7: Operational performance is positively associated with business performance.

H8a–H8c: Operational performance mediates the relationships of demand analytics, digital inventory management and supply chain responsiveness, respectively, with business performance.

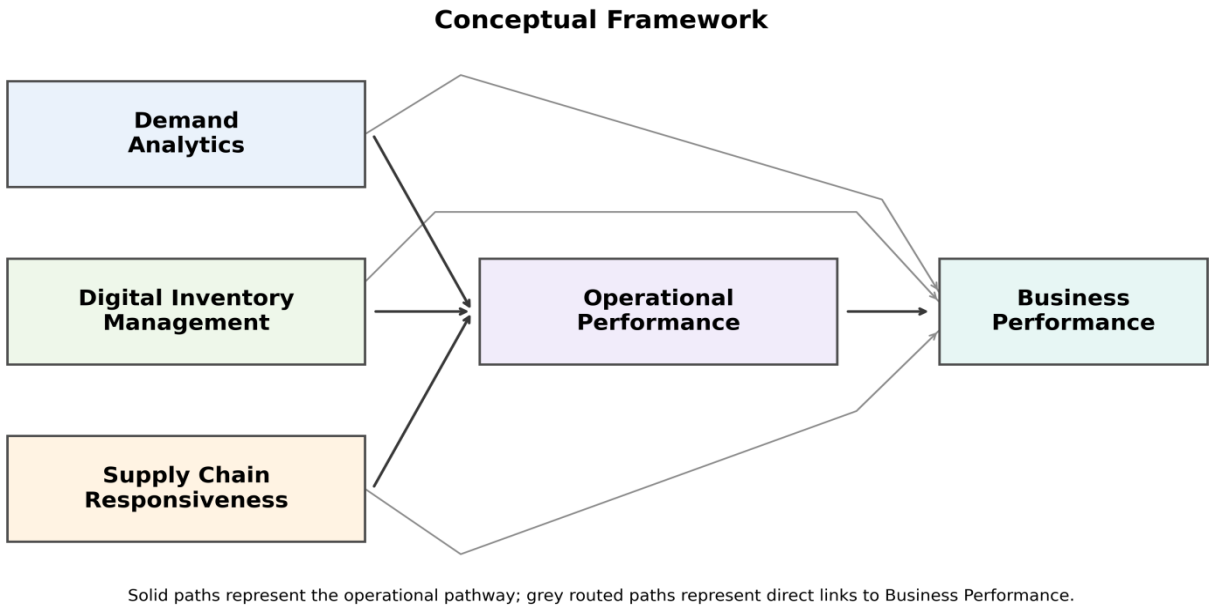


Figure 1. Conceptual framework linking digital supply-chain capabilities with Operational Performance and Business Performance.

Data and Methodology

Data source and analytical sample

The empirical analysis uses the openly deposited dataset "Enhancing Operational Efficiency in the Fast Fashion E-Commerce Industry: The Role of Demand Analytics, Digital Inventory Management, and Supply Chain Responsiveness" [1]. The repository describes a quantitative explanatory study of 187 owners and managers of selected fast-fashion retail establishments operating in e-commerce. The uploaded CSV contains 187 complete respondent rows and 27 questionnaire items. The present analysis uses the raw item responses directly and does not alter observations to obtain statistical significance.

Measurement

Five composite constructs were created from the original item prefixes: Demand Analytics (DA1–DA6), Digital Inventory Management (DIM1–DIM6), Supply Chain Responsiveness (SCR1–SCR5), Operational Performance (OP1–OP5), and Business Performance (BP1–BP5). Each composite is the arithmetic mean of its constituent items. This preserves the source dataset's measurement structure. Internal consistency was evaluated using Cronbach's alpha. The analysis intentionally uses the label Business Performance rather than Business Excellence because the uploaded dataset contains a BP scale, not a separately validated business-excellence construct.

Statistical strategy

The analysis proceeded in five stages. First, reliability, descriptive statistics and Pearson correlations were calculated. Second, Model 1 regressed Operational Performance on Demand Analytics, Digital Inventory Management and Supply Chain Responsiveness. Third, Model 2 regressed Business Performance on the three capabilities plus Operational Performance. Standardized coefficients were obtained by estimating the same models on z-standardized composite scores. Fourth, diagnostics examined variance inflation factors, residual normality, heteroskedasticity and influential observations. Because the Breusch–Pagan test detected heteroskedasticity in the final model, HC3 heteroskedasticity-consistent standard errors were reported as a robustness check [33,34]. A sensitivity model excluding observations with Cook's distance greater than 4/n was also estimated [35]. Fifth, indirect effects were calculated as the product of the relevant a-path (capability → Operational Performance) and b-path (Operational Performance → Business Performance controlling for the capabilities), with percentile 95% confidence intervals from 5,000 non-parametric bootstrap resamples [29–32].

Regression equations

The operational model is $OP = \beta_0 + \beta_1 DA + \beta_2 DIM + \beta_3 SCR + \varepsilon$. The final business-performance model is $BP = \beta_0 + \beta_1 DA + \beta_2 DIM + \beta_3 SCR + \beta_4 OP + \varepsilon$. Mediation is supported when the bootstrap confidence interval for an indirect effect does not include zero. Given the cross-sectional design, the terms "effect" and "mediation" refer to statistical pathway estimates and should not be interpreted as definitive causal effects.

Results

Reliability and descriptive statistics

Table 1 presents the descriptive statistics and Cronbach's alpha values for all five study constructs.

Construct	Items	Mean	SD	Cronbach's α
Demand Analytics	6	3.912	0.795	0.936
Digital Inventory Management	6	4.119	0.753	0.922
Supply Chain Responsiveness	5	3.521	0.985	0.920
Operational Performance	5	4.319	0.575	0.924
Business Performance	5	4.305	0.562	0.923

Table 1. Construct descriptive statistics and internal consistency.

All five scales showed high internal consistency, with Cronbach's alpha ranging from 0.920 to 0.936. The reliability results support aggregation of the item blocks into composite means for the subsequent regression and mediation analyses.

Correlations

The bivariate relationships among Demand Analytics, Digital Inventory Management, Supply Chain Responsiveness, Operational Performance, and Business Performance are reported in Table 2.

Construct	DA	DIM	SCR	OP	BP
DA	1.000	0.554	0.504	0.536	0.675
DIM	0.554	1.000	0.546	0.537	0.705
SCR	0.504	0.546	1.000	0.478	0.639
OP	0.536	0.537	0.478	1.000	0.798
BP	0.675	0.705	0.639	0.798	1.000

Table 2. Pearson correlation matrix.

All focal constructs were positively correlated. Business Performance correlated with Demand Analytics (r=0.675), Digital Inventory Management (r=0.705), Supply Chain Responsiveness (r=0.639) and Operational Performance (r=0.798). The correlations are substantial but do not by themselves indicate problematic multicollinearity; this was assessed formally using variance inflation factors.

Operational Performance regression

Table 3 reports the regression coefficients, standardized effects, significance levels, and 95% confidence intervals for the Operational Performance model.

Predictor	B	SE	β	t	p	95% CI
Demand Analytics	0.212	0.052	0.293	4.04	< .001	[0.108, 0.315]
Digital Inventory Management	0.212	0.057	0.277	3.71	< .001	[0.099, 0.324]
Supply Chain Responsiveness	0.105	0.042	0.179	2.49	= 0.014	[0.022, 0.187]

Table 3. Ordinary least squares regression predicting Operational Performance.

Model 1 was statistically significant, $F(3,183)=39.18$, $p<.001$, $R^2=0.391$, adjusted $R^2=0.381$. Demand Analytics (B=0.212, p<.001), Digital Inventory Management (B=0.212, p<.001), and Supply Chain Responsiveness (B=0.105, p=0.014) were positive predictors. Thus H1, H2 and H3 were supported.

The estimated operational equation is: OP = 2.251 + 0.212(DA) + 0.212(DIM) + 0.105(SCR).

Final Business Performance regression

The estimates for the final Business Performance regression model are presented in Table 4.

Predictor	B	SE	β	t	p	95% CI
Demand Analytics	0.137	0.031	0.193	4.43	< .001	[0.076, 0.197]
Digital Inventory Management	0.181	0.033	0.242	5.42	< .001	[0.115, 0.247]
Supply Chain Responsiveness	0.104	0.024	0.181	4.30	< .001	[0.056, 0.151]
Operational Performance	0.467	0.042	0.478	11.21	< .001	[0.385, 0.550]

Table 4. Final ordinary least squares regression predicting Business Performance.

The final model was highly significant, $F(4,182)=180.13$, $p<.001$, and explained 79.8% of the observed variance in Business Performance ($R^2=0.798$; adjusted $R^2=0.794$). Demand Analytics ($B=0.137$, $p<.001$), Digital Inventory Management ($B=0.181$, $p<.001$), Supply Chain Responsiveness ($B=0.104$, $p<.001$), and Operational Performance ($B=0.467$, $p<.001$) all remained positive when estimated simultaneously.

The requested final regression equation is: BP = 0.643 + 0.137(DA) + 0.181(DIM) + 0.104(SCR) + 0.467(OP). Operational Performance had the largest standardized coefficient ($\beta=0.478$), followed by Digital Inventory Management ($\beta=0.242$), Demand Analytics ($\beta=0.193$) and Supply Chain Responsiveness ($\beta=0.181$).

Regression diagnostics and robustness checks

Regression diagnostics are reported in Tables 5 and 6. Table 5 presents the variance inflation factors used to assess multicollinearity, whereas Table 6 reports HC3 heteroskedasticity-robust inference. The residual-versus-fitted pattern for the final model is shown in Figure 2.

Predictor	Variance inflation factor
Demand Analytics	1.71
Digital Inventory Management	1.80
Supply Chain Responsiveness	1.61
Operational Performance	1.64

Table 5. Multicollinearity diagnostics for the final Business Performance model.

Variance inflation factors ranged from 1.61 to 1.80, well below commonly used warning thresholds, indicating that the high R^2 is not explained by severe multicollinearity. The Jarque–Bera test did not reject residual normality ($JB=0.434$, $p=0.805$). The Breusch–Pagan test did, however, indicate heteroskedasticity ($LM=29.96$, $p<.001$). For this reason, HC3 robust standard errors were estimated.

Predictor	B	HC3 SE	Robust p
Demand Analytics	0.137	0.034	< .001
Digital Inventory Management	0.181	0.034	< .001
Supply Chain Responsiveness	0.104	0.023	< .001
Operational Performance	0.467	0.072	< .001

Table 6. Heteroskedasticity-robust inference for the final model.

All four predictors remained statistically significant under HC3 inference. Influence diagnostics identified 11 observations above the conventional Cook's-distance screening value of $4/n$ (0.021). Excluding those observations reduced R^2 to 0.691, but all four coefficients remained positive and statistically significant (all $p<.001$). This sensitivity analysis indicates that the substantive direction and significance of the findings are not dependent on the identified influential observations, although the magnitude of explained variance is lower in the restricted sample.

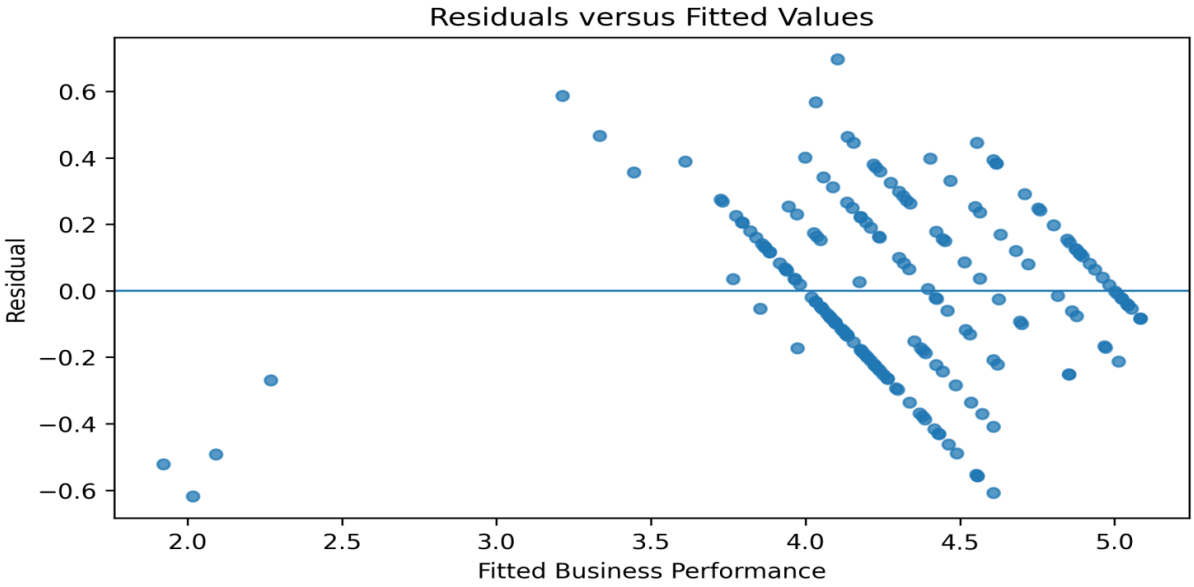


Figure 2. Residual-versus-fitted diagnostic for the final Business Performance regression model.

Mediation analysis

Table 7 reports the bootstrapped indirect effects of Demand Analytics, Digital Inventory Management, and Supply Chain Responsiveness on Business Performance through Operational Performance.

Predictor	a path	b path	Indirect effect	Bootstrap 95% CI	Decision
Demand Analytics	0.212	0.467	0.099	[0.038, 0.170]	Significant
Digital Inventory Management	0.212	0.467	0.099	[0.029, 0.173]	Significant
Supply Chain Responsiveness	0.105	0.467	0.049	[0.012, 0.095]	Significant

Table 7. Bootstrap indirect effects through Operational Performance (5,000 resamples).

The indirect effect of Demand Analytics on Business Performance through Operational Performance was 0.099 (95% bootstrap CI [0.038, 0.170]). The corresponding indirect effect for Digital Inventory Management was 0.099 (95% CI [0.029, 0.173]), and for Supply Chain Responsiveness it was 0.049 (95% CI [0.012, 0.095]). None of the intervals included zero, supporting H8a–H8c. Because the direct capability coefficients in the final BP model also remained positive and significant, the pattern is consistent with partial statistical mediation rather than complete mediation.

Hypothesis summary

The decisions for all direct and mediation hypotheses are consolidated in Table 8.

Hypothesis	Relationship	Decision
H1	Demand Analytics → Operational Performance	Significant (Supported)
H2	Digital Inventory Management → Operational Performance	Significant
H3	Supply Chain Responsiveness → Operational Performance	Significant
H4	Demand Analytics → Business Performance	Significant
H5	Digital Inventory Management → Business Performance	Significant

H6	Supply Chain Responsiveness → Business Performance	Significant
H7	Operational Performance → Business Performance	Significant
H8a	DA → OP → BP indirect pathway	Significant
H8b	DIM → OP → BP indirect pathway	Significant
H8c	SCR → OP → BP indirect pathway	Significant

Table 8. Hypothesis decisions based on the observed data.

Discussion

The findings provide a coherent picture of how digital supply-chain capabilities relate to performance in the analyzed fast-fashion e-commerce sample. Demand Analytics, Digital Inventory Management and Supply Chain Responsiveness were all positively associated with Operational Performance, and the operational model explained a meaningful share of variance. This supports the view that digital capability is valuable when it improves the quality and speed of operational decision making rather than existing as a stand-alone technology investment [8,9,12–14].

The Business Performance model extends this result. All three digital supply-chain capabilities retained positive coefficients after Operational Performance was introduced, while Operational Performance itself was the strongest standardized predictor. This distinction matters theoretically. It suggests that the business value of digital supply-chain capability is not reducible to a single direct path. Instead, capability and execution appear to operate together: digital capabilities have direct associations with Business Performance and additional indirect associations through Operational Performance.

The Demand Analytics result is consistent with the resource-based and information-processing perspectives. Analytics expands the firm's capacity to process demand information under uncertainty [4,8]. Yet data alone do not create value. The mediation result indicates that part of the association between analytics and Business Performance is transmitted through better operational execution. This is compatible with prior evidence that analytics capability produces performance benefits through dynamic capabilities, resilience, innovation or knowledge-development mechanisms [9,12–14,18].

Digital Inventory Management showed the largest direct coefficient among the three digital capability variables in the final Business Performance model. In a fast-fashion e-commerce context, this is plausible because inventory availability, allocation and replenishment have immediate implications for sales capture, markdown exposure and service reliability. Recent evidence that digital infrastructure can reduce inventory intensity [27] and that digitally enabled inventory systems can influence financial outcomes reinforces the strategic importance of inventory information. The present result should nevertheless be interpreted as an association within the questionnaire sample rather than as proof that adopting a particular inventory technology will cause a specific financial gain.

Supply Chain Responsiveness was also positively associated with both outcomes. Its coefficient was smaller than those of Demand Analytics and Digital Inventory Management, but it remained statistically significant in the simultaneous models and under robust inference. This finding aligns with the broader agility and resilience literature, where the performance value of digitalization frequently depends on the organization's ability to respond, adapt and recover [11,16,22–25]. Responsiveness may therefore be understood as a behavioral manifestation of digital capability: information becomes valuable when the supply chain can act on it.

The mediation findings are particularly important. The bootstrap confidence intervals for all three indirect effects excluded zero, and the direct coefficients remained significant after Operational Performance was included. This is a partial-mediation pattern. It implies that Operational Performance is an important transmission pathway but not the only one. Demand analytics may also improve strategic decision quality; inventory digitalization may affect availability and working capital; and responsiveness may affect customer experience or market adaptation directly. This multi-pathway interpretation is more defensible than claiming that all business benefits occur solely through operations.

The high R^2 of the final model deserves explicit scrutiny. An R^2 near .80 can reflect genuinely strong relationships among related managerial constructs, but it can also raise concerns about common-method variance, overlapping measurement or influential cases. The diagnostics reduce—but do not eliminate—these concerns. Variance inflation factors are low, so severe predictor collinearity is not driving the result. Residuals are approximately normal, and all coefficients survive HC3 heteroskedasticity-

robust inference. Removing observations exceeding the conventional Cook's-distance screen lowers R^2 but leaves every focal coefficient positive and significant. These checks strengthen confidence that the central relationships are not a simple artifact of one diagnostic problem.

At the same time, the Breusch–Pagan result shows that conventional homoskedastic regression assumptions are imperfect. Reporting HC3 robust standard errors is therefore important. More broadly, all constructs are self-reported and collected in the same questionnaire, which can inflate associations through common-method processes. The present paper responds by being conservative in its causal language and by distinguishing statistical mediation from causal mediation. Longitudinal, multi-source and objective-performance designs are needed before stronger causal claims are warranted.

The study also contributes to the distinction between Operational Performance and Business Performance. Supply-chain studies sometimes collapse performance into a single outcome, yet foundational integration research and digital performance frameworks recognize multiple performance layers [7,10]. By estimating the two outcomes separately, the analysis shows that the same capabilities can relate to process execution and broader business results in different ways. This is also why the manuscript does not rename the BP construct as "Business Excellence." Business excellence is a broader normative and organizational concept; the present data support a Business Performance model.

Theoretical Implications

First, the findings support a complementary-capabilities interpretation of the resource-based view. The predictors are not simply technology adoption indicators; they represent organizational routines for interpreting demand, managing inventory information and responding to change. Their simultaneous significance suggests that digital supply-chain advantage is distributed across multiple capabilities rather than concentrated in a single technological resource.

Second, the results extend dynamic-capabilities reasoning by locating Operational Performance between capability and Business Performance. Demand Analytics can be interpreted as sensing, digital inventory management as digitally enabled seizing and coordination, and responsiveness as rapid adjustment. The significant indirect paths indicate that these capabilities are associated with business outcomes partly through their relationship with operational execution.

Third, the findings support information-processing theory in a context characterized by uncertainty and rapid product cycles. Demand analytics increases information-processing capacity; digital inventory management improves the visibility and accessibility of execution information; responsiveness enables action. The integrated model therefore connects information processing with execution and business outcomes in one empirically testable structure.

Managerial Implications

Managers should avoid treating analytics, inventory digitalization and responsiveness as separate digital projects. The results suggest that their value is interconnected. Demand analytics should be linked to replenishment and allocation decisions; inventory systems should provide timely information to decision makers; and operating processes should be designed to respond to the resulting signals. A dashboard that tracks only technology adoption without operational outcomes would miss the mechanism identified in the mediation analysis.

The Business Performance equation can be used as a descriptive summary of the sample relationships: BP = 0.643 + 0.137(DA) + 0.181(DIM) + 0.104(SCR) + 0.467(OP). It should not be used as a universal forecasting rule because the coefficients are sample-specific and cross-sectional. Its managerial value lies in showing that Operational Performance has the largest conditional association with Business Performance while each digital capability also retains a direct positive association.

From an implementation perspective, the findings favor staged digital transformation. Firms can first strengthen data quality and demand visibility, then integrate these signals with inventory decisions, and finally ensure that processes have the authority and flexibility to respond. Performance measurement should include both proximal operational indicators and broader business outcomes so that managers can identify where a digital initiative is creating—or failing to create—value.

Limitations and Future Research

The study has several limitations. First, the design is cross-sectional, so temporal ordering is not observed. Statistical mediation is therefore evidence of an indirect association consistent with the proposed mechanism, not proof of causal mediation. Future research should use longitudinal designs in which digital capabilities are measured before operational and business outcomes.

Second, all variables are based on questionnaire responses from the same respondents. This creates potential common-method variance and perceptual bias. Future studies should combine survey measures with objective indicators such as forecast error, stock-out rate, inventory turnover, order-cycle time, return rates, sales growth or profitability.

Third, the sample contains 187 owners and managers in a specific fast-fashion e-commerce setting. The results may not generalize to capital-intensive manufacturing, healthcare, food, construction or public-sector supply chains. Multi-country and multi-industry replication would clarify boundary conditions.

Fourth, the final model exhibits heteroskedasticity and several influential observations. HC3 inference and influence sensitivity analyses show that the main conclusions are robust, but future work should examine non-linear relationships, latent-variable models and distributional heterogeneity. Structural equation modeling could also explicitly model measurement error and compare alternative mediation structures.

Finally, Business Performance should not be treated as synonymous with Business Excellence. A future study designed specifically around business excellence should include validated dimensions such as leadership, strategy, people, partnerships/resources, process management, customer results and financial/non-financial outcomes. Such a design would allow the client's broader "Business Excellence" terminology to be tested directly rather than inferred from a BP scale.

Conclusion

This study provides a complete empirical test of a digital supply-chain performance model using 187 respondent-level observations. Demand Analytics, Digital Inventory Management and Supply Chain Responsiveness were each positively associated with Operational Performance, and Operational Performance was in turn strongly associated with Business Performance. The final Business Performance model explained 79.8% of variance and produced the equation BP = 0.643 + 0.137(DA) + 0.181(DIM) + 0.104(SCR) + 0.467(OP). All direct hypotheses were supported by the observed data. Bootstrap mediation further showed positive indirect pathways from each digital capability to Business Performance through Operational Performance. Multicollinearity was low, residual normality was acceptable, HC3 robust inference preserved the significance of all focal coefficients, and an influence sensitivity analysis preserved the direction and significance of the findings. Taken together, the results support an integrated interpretation in which digital supply-chain capabilities contribute to business outcomes both directly and through stronger operational execution. The conclusions remain associational because the data are cross-sectional, but the revised analysis provides a substantially stronger and more transparent empirical foundation than a model that treats operational and business performance as the same construct.

References

1. Khalisha, R. A., & Triana, I. (2026). Enhancing Operational Efficiency in the Fast Fashion E-Commerce Industry: The Role of Demand Analytics, Digital Inventory Management, and Supply Chain Responsiveness [Data set]. Zenodo. https://doi.org/10.5281/zenodo.20667908
2. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108
3. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z
4. Galbraith, J. R. (1974). Organization design: An information processing view. Interfaces, 4(3), 28–36.
5. Cooper, M. C., Lambert, D. M., & Pagh, J. D. (1997). Supply chain management: More than a new name for logistics. The International Journal of Logistics Management, 8(1), 1–14. https://doi.org/10.1108/09574099710805556
6. Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Rao, S. S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. Omega, 34(2), 107–124. https://doi.org/10.1016/j.omega.2004.08.002
7. Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. Journal of Operations Management, 28(1), 58–71. https://doi.org/10.1016/j.jom.2009.06.001

8. Chae, B. K., Olson, D., & Sheu, C. (2014). The impact of supply chain analytics on operational performance: A resource-based view. International Journal of Production Research, 52(16), 4695–4710. https://doi.org/10.1080/00207543.2013.861616

9. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

10. Rasool, F., Greco, M., & Grimaldi, M. (2022). Digital supply chain performance metrics: A literature review. Measuring Business Excellence, 26(1), 23–38. https://doi.org/10.1108/MBE-11-2020-0147

11. Qader, G., Junaid, M., Abbas, Q., & Mubarik, M. S. (2022). Industry 4.0 enables supply chain resilience and supply chain performance. Technological Forecasting and Social Change, 185, 122026. https://doi.org/10.1016/j.techfore.2022.122026

12. Bhatti, S. H., Wan Hussain, W. M. H., Khan, J., Sultan, S., & Ferraris, A. (2024). Exploring data-driven innovation: What's missing in the relationship between big data analytics capabilities and supply chain innovation? Annals of Operations Research, 333, 799–824. https://doi.org/10.1007/s10479-022-04772-7

13. Gopal, P. R. C., Rana, N. P., Krishna, T. V., & Ramkumar, M. (2024). Impact of big data analytics on supply chain performance: An analysis of influencing factors. Annals of Operations Research, 333, 769–797. https://doi.org/10.1007/s10479-022-04749-6

14. Bahrami, M., Shokouhyar, S., & Seifian, A. (2022). Big data analytics capability and supply chain performance: The mediating roles of supply chain resilience and innovation. Modern Supply Chain Research and Applications, 4(1), 62–84. https://doi.org/10.1108/MSCRA-11-2021-0021

15. Khan, S. A. R., Ahmad, Z., Sheikh, A. A., & Yu, Z. (2022). Digital transformation, smart technologies, and eco-innovation are paving the way toward sustainable supply chain performance. Science Progress, 105(4), 00368504221145648. https://doi.org/10.1177/00368504221145648

16. Rahman, M. S., Gani, M. O., Fatema, B., & Takahashi, Y. (2023). B2B firms' supply chain resilience orientation in achieving sustainable supply chain performance. Sustainable Manufacturing and Service Economics, 2, 100011. https://doi.org/10.1016/j.smse.2023.100011

17. Bhadoria, G. S., Singh, S., Daultani, Y., & Chouhan, M. (2023). Measuring the influence of digital twins on the sustainability of manufacturing supply chain: A mediating role of supply chain resilience and performance. Computers & Industrial Engineering, 186, 109711. https://doi.org/10.1016/j.cie.2023.109711

18. Fantazy, K., & Tipu, S. A. A. (2024). Linking big data analytics capability and sustainable supply chain performance: Mediating role of knowledge development. Management Research Review, 47(4), 512–536. https://doi.org/10.1108/MRR-01-2023-0018

19. Ali, S. M., Rahman, A. U., Kabir, G., & Paul, S. K. (2024). Artificial Intelligence Approach to Predict Supply Chain Performance: Implications for Sustainability. Sustainability, 16(6), 2373. https://doi.org/10.3390/su16062373

20. Rashid, A., Kazi, A. K., & Ramish, M. S. (2024). Impact of Artificial Intelligence on Supply Chain Performance: Mediation Role of Supply Chain Resilience. Pakistan Social Sciences Review, 8(4), 408–418. https://doi.org/10.35484/pssr.2024(8-IV)32

21. Rehman, S.-U., Barson, N., & Hamdan, Y. H. (2024). Industry 4.0 Technologies and Firm Performance with Digital Supply Chain Platforms and Supply Chain Capabilities. Pakistan Journal of Commerce and Social Sciences, 18(4), 893–924. https://doi.org/10.64534/Comm.2025.021

22. Rana, J., Daultani, Y., Goswami, M., & Kumar, S. (2025). Exploring the Impact of Supply Chain Digital Transformation on Supply Chain Performance: An Empirical Investigation. Business Strategy and the Environment, 34, 3497–3521. https://doi.org/10.1002/bse.4157

23. Abdallah, A. B., Almomani, H. A., & Al-Zu'bi, Z. M. F. (2025). Industry 4.0-Enabled Supply Chain Performance: Do Supply Chain Capabilities and Innovation Matter? Logistics, 9(1), 36. https://doi.org/10.3390/logistics9010036

24. Li, P., Chen, Y., & Guo, X. (2025). Digital transformation and supply chain resilience. International Review of Economics & Finance, 99, 104033. https://doi.org/10.1016/j.iref.2025.104033

25. Aslam, H., Rehman, A. U., Iftikhar, A., Haq, M. Z. U., Akbar, U., & Kamal, M. M. (2025). Digital transformation: Unlocking supply chain resilience through adaptability and innovation. Technological Forecasting and Social Change, 124234. https://doi.org/10.1016/j.techfore.2025.124234

26. Tian, Y., & Cui, L. (2025). Supply chain resilience and digital transformation: Perspectives from a supply chain network. Humanities and Social Sciences Communications, 12, 1738.

27. Huraeji, J., & Fitriyah, H. (2025). The role of AI, IoT, and RFID-based digital inventory control systems in improving operational and financial performance. International Journal of Economic Integration and Regional Competitiveness, 2(11), 76–95. https://doi.org/10.61796/ijeirc.v2i11.428

28. Jha, A. K., Verma, N. K., & Bose, I. (2022). Measuring and managing digital supply chain performance. In Digital Supply Chains (pp. 199–214). Elsevier. https://doi.org/10.1016/B978-0-323-91614-1.00012-5

29. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate Data Analysis (8th ed.). Cengage.

30. Hayes, A. F. (2022). Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach (3rd ed.). Guilford Press.

31. MacKinnon, D. P. (2008). Introduction to Statistical Mediation Analysis. Routledge.

32. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

33. White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 48(4), 817–838. https://doi.org/10.2307/1912934

34. Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica, 47(5), 1287–1294. https://doi.org/10.2307/1911963

35. Cook, R. D. (1977). Detection of influential observation in linear regression. Technometrics, 19(1), 15–18. https://doi.org/10.1080/00401706.1977.10489493



2026 by the authors; Journal of Global Social Transformation (JGST). This is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (http://creativecommons.org/licenses/by/4.0/).