System Quality, Information Quality and Support/Training: Effects on Logistics Process Performance

Mohammed Riad
Management Sciences, Phd Candidate, Faculty of Legal, Economicand Social Sciences, Ain Sebaa, Hassan Ii University of Casablanca, Laboratory Maege, Department of Statistics and Applied Mathematics, Morocco
ORCID: 0009-0003-1721-5622
Hicham El Bouanani
Professor / Researcher, Faculty of Legal, Economic and Social Sciences, Ain Sebaa, Hassan Ii University of Casablanca, Laboratory Maege, Department of Statistics and Applied Mathematics, Morocco
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Abstract

In a context of accelerating digitalization of logistics and supply chains, organizations expect information systems (ERP, WMS, TMS) to deliver tangible efficiency gains (shorter lead times, higher productivity, fewer errors). However, such benefits depend less on the mere presence of tools than on perceived system quality, perceived information quality, and the level of support/training provided to users. Drawing on the information systems success literature (DeLone & McLean, 2003; Petter et al., 2008), this study examines the effects of system quality (QS), information quality (QI), and support/training (SF) on process performance (EP). Based on a 5-point Likert survey administered to N = 227 professionals, we estimate hierarchical multiple regression models with HC3 robust standard errors (MacKinnon & White, 1985). Results show positive and significant effects of QS (B = 0.339, p < 0.001), QI (B = 0.402, p < 0.001), and SF (B = 0.204, p = 0.002) on EP in the full model (R2 = 0.506), while tested moderation effects are not significant. Common method bias checks and diagnostic tests (VIF, Breusch-Pagan, Shapiro-Wilk, influential observations) complement the analysis and support the robustness of conclusions.

Keywords: *system quality, information quality, support/training, process performance, logistics, robust regression, MLR.*

1. Introduction

Digital transformation is profoundly reshaping logistics operations, notably through the widespread adoption of ERP, WMS, TMS, collaborative platforms, and connected devices that are expected to increase visibility, traceability, and flow synchronization - thereby reducing lead times, improving productivity, and limiting execution errors (Helo & Thai, 2024; turkes, 2025; Wang et al., 2025). Yet field experience shows that these benefits are neither automatic nor uniform: unstable, poorly ergonomic, or insufficiently available systems can trigger workarounds, under-use, and operational frictions, while incomplete, outdated, or perceived-unreliable data undermine planning, coordination, and decision quality (Mishrif & Khan, 2023). In other words, performance does not depend solely on the presence of a tool, but on the quality of the surrounding socio-technical arrangement: the system's technical quality, the quality of the information produced, and the conditions under which users appropriate the technology (De Lone & McLean, 2003; Petter et al., 2008; Venkatesh et al., 2003).

From this perspective, the information systems (IS) success literature provides a particularly relevant lens to explain how system and information characteristics translate into net benefits (De Lone & McLean, 2003; Petter et al., 2008; Seddon, 1997). Applied to logistics processes, this approach suggests that system quality (reliability, availability, response time, ease of use) and information quality (accuracy, completeness, timeliness, relevance) are proximate determinants of operational indicators such as cycle time, error rate, and productivity (Li & Lin, 2006; Wixom & Todd, 2005). In parallel, research on logistics performance measurement emphasizes the importance of a process-centered reading grounded in execution metrics, in order to capture value creation beyond financial outcomes alone (Gunasekaran & Kobu, 2007; Gunasekaran et al., 2001; Neely et al., 1995). Despite these contributions, two aspects remain insufficiently stabilized in logistics-oriented studies: (i) the explicit integration of support/training as an appropriation condition that may directly influence performance, and (ii) the robustness of statistical inference in cross-sectional, perception-based designs, where risks of heteroskedasticity and common method bias should be addressed systematically (Fuller et al., 2016; Podsakoff et al., 2003).

This study evaluates, on a sample of 227 professionals, to what extent perceived system quality (QS), perceived information quality (QI), and support/training (SF) explain logistics process performance (EP), using hierarchical multiple regression with HC3 robust standard errors (MacKinnon & White, 1985; White, 1980). We also test whether support/training strengthens the effects of system quality and information quality on

performance (interaction effects), while documenting the validity of results through standard diagnostics (multi collinearity, heteroskedasticity, residual normality, influential observations). In doing so, the article contributes to a more fine-grained understanding of performance levers in digitalized logistics by showing that operational value results from alignment between technical reliability, data governance, and user-support mechanisms.

2. Literature review and hypothesis development

2.1 Logistics digitalization and process performance

"Logistics 4.0" initiatives and, more broadly, the digitalization of supply chains aim to improve cross-functional coordination, partner integration, and decision efficiency through better flow visibility (Helo & Thai, 2024; turkes, 2025; Wang et al., 2025). However, recent work highlights that outcomes depend strongly on deployment modalities and the organizational environment: digitization policies that are insufficiently aligned with work routines and data-governance requirements can limit effective adoption and reduce expected gains (Mishrif & Khan, 2023). In this context, analyzing performance at the process level (lead times, productivity, errors) is particularly appropriate because these indicators directly capture the execution quality of logistics activities (Gunasekaran & Kobu, 2007; Gunasekaran et al., 2001; Neely et al., 1995).

2.2 IS success as an explanatory Framework

The IS success model (DeLone& McLean, 2003) and its extensions (Petter et al., 2008; Seddon, 1997) posit that system value results from a chain linking qualities (system, information, service), use/satisfaction, and net benefits. In operational contexts, technical system quality and information quality are often treated as proximal antecedents of performance because they condition transaction reliability, feature availability, and decision relevance (Wixom & Todd, 2005). Moreover, integration with technology acceptance research suggests that appropriation (ease of use, perceived usefulness, facilitating conditions) shapes the realization of benefits (Venkatesh et al., 2003). Applied to logistics, this framework leads us to treat performance as the outcome of socio-technical alignment among the tool, the data, and usage practices.

2.3 System quality and process performance

System quality refers to perceived technical performance (reliability, availability, response time, usability, compatibility) (DeLone & McLean, 2003). In logistics operations, these attributes reduce interruptions, streamline execution (receiving, put-away, picking, shipping), and limit errors related to malfunctions

and processing delays, which should improve process performance. High system quality also reinforces routine standardization and traceability - two critical dimensions in coordination-intensive environments (Wixom & Todd, 2005). H1: System quality (QS) has a positive effect on process performance (EP).

2.4 Information quality and process performance

Information quality refers to the accuracy, completeness, timeliness, relevance, and accessibility of data used to steer activities (Wixom & Todd, 2005). In supply chains, higher-quality information reduces uncertainty, improves planning, and facilitates coordination, translating into operational gains (shorter lead times, better service, fewer errors) (Li & Lin, 2006). Several studies show that information quality supports performance, sometimes through mechanisms such as integration or information sharing (Chavez et al., 2015; Kankam et al., 2023; Marinagi et al., 2015). H2: Information quality (QI) has a positive effect on process performance (EP).

2.5 Support/training, appropriation, and performance

Support/training encompasses the resources that help users understand processes, resolve incidents, master functionalities, and sustain skills over time. From an IS success perspective, such mechanisms are close to the "service quality" dimension and influence satisfaction and continued use (DeLone & McLean, 2003; Petter et al., 2008). In logistics environments - where execution relies on frequent IS interactions and usage errors can be costly - support/training may directly enhance performance by reducing mistakes, accelerating problem resolution, and strengthening compliance with data-entry and processing standards. H3: Support/training (SF) has a positive effect on process performance (EP).

2.6 Expected contingent role of support/training

Beyond direct effects, support/training may theoretically strengthen the impact of technical and informational qualities on performance: better-trained users can exploit system functionalities more fully and are better able to produce and use reliable data, which could increase the marginal returns of system quality and information quality (Venkatesh et al., 2003). Empirical evidence, however, is mixed: in some contexts, support/training acts more as an autonomous determinant of performance than as an amplifier of quality effects - especially when support variability is limited or when more complex mechanisms (e.g., mediation through actual use) are at play (Petter et al., 2008). We nevertheless formulate moderation hypotheses to be tested empirically. H4:

Support/training (SF) positively strengthens the effect of QS on EP (QS×SF).
H5: Support/training (SF) positively strengthens the effect of QI on EP (QI×SF).

2.7 Conceptual model

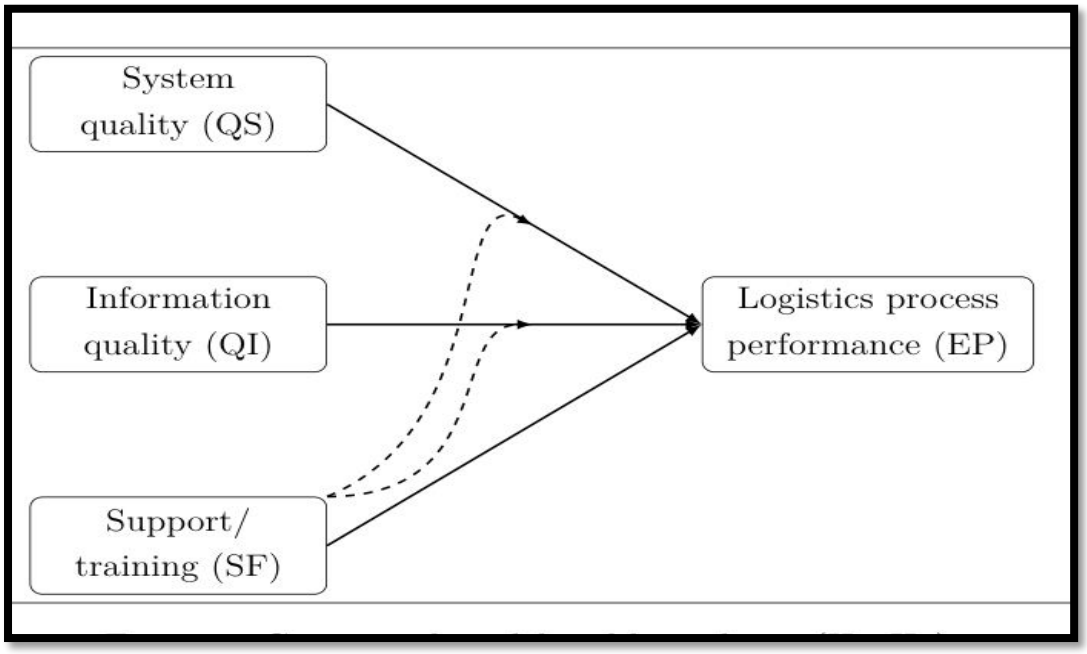


Figure 1: Conceptual model and hypotheses (H1–H5)

The conceptual model follows the IS success perspective, according to which net operational benefits result from alignment between the system's technical quality, the quality of the information mobilized, and user appropriation conditions. In a logistics environment - where activities are sequenced and interdependent - system quality (reliability, availability, response time, usability, compatibility) should reduce execution disruptions, limit workarounds, and increase transaction fluidity. Information quality (accuracy, completeness, timeliness, relevance) is a central determinant of coordination and planning because it conditions decision-making, flow synchronization, and error control. Finally, support/training represents an enabling mechanism that fosters competence building, rapid incident resolution, and standardized data-entry practices, which can directly improve process performance.
Beyond the expected direct effects (H1-H3), we test a contingent role of support/training (H4-H5): better-trained users may exploit system functionalities more fully and produce/consume higher-quality data, potentially reinforcing the marginal impact of system quality and information quality on performance. Empirically, these propositions are examined by estimating main effects (QS, QI, SF) and interaction terms (QS×SF, QI×SF) on process performance (EP).

3. Methodology

3.1 Research design, instrument, and data collection

The study adopts a cross-sectional quantitative design based on a self-administered questionnaire. Items are measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The constructs QS, QI, and SF are measured with multi-item scales adapted from the IS literature (DeLone & McLean, 2003; Wixom & Todd, 2005). The dependent variable EP captures perceived process performance.

3.2 Sample

Table 1 summarizes the sample profile (N = 227) in terms of role, tenure, sector, firm size, usage frequency, and self-rated proficiency.

Table 1: Descriptive profile of the sample (N=227).

Variable	Category	N	%
role	Logistics manager	53	23.300
role	Procurement/Purchasing	41	18.100
role	Warehousing/Storage	32	14.100
role	Transportation	25	11.000
role	Production	23	10.100
role	Quality/Continuous Improvement	18	7.900
role	IT/Information Systems	15	6.600
role	Other	20	8.800
tenure	< 1 year	21	9.300
tenure	1-3 years	68	30.000
tenure	3-5 years	54	23.800
tenure	> 5 years	84	37.000
sector	Industry	65	28.600
sector	Retail/Distribution	51	22.500
sector	Services	47	20.700
sector	Transportation/Logistics	36	15.900
sector	Healthcare	16	7.000
sector	Other	12	5.300
firm size	< 50	52	22.900
firm size	50-249	88	38.800
firm size	250-999	54	23.800
firm size	>= 1000	33	14.500
usage frequency	Daily	121	53.300
usage frequency	Several times/week	66	29.100
usage frequency	Once/week	25	11.000
usage frequency	Rarely	15	6.600

proficiency	Low	28	12.300
proficiency	Medium	121	53.300
proficiency	Good	63	27.800
proficiency	Excellent	15	6.600
system	ERP	109	48.000
system	WMS	46	20.300
system	TMS	31	13.700
system	Other/Multiple	41	18.100

These descriptive characteristics indicate a sufficiently diverse respondent base, which reduces the risk of drawing conclusions from an overly specific subgroup. The distribution across key profile attributes supports the relevance of the analysis for differentiated organizational contexts. Such heterogeneity is useful for examining managerial and informational mechanisms that may vary with roles and experience. It also strengthens external validity by reflecting a realistic diversity of work situations. Moreover, a relatively balanced profile attenuates systematic bias that could over- or under-estimate perceived logistics performance. Overall, the sample structure provides a credible basis for testing the proposed relationships.

3.3 Analysis plan

3.3.1 Descriptive statistics

Table 2: Descriptive statistics of constructs (means).

Construct	Mean	SD	Min	Max	Skewness	Kurtosis
QS_mean	2.98	0.837	1.167	4.833	-0.141	-0.747
QI_mean	3.084	0.814	1.0	5.0	-0.022	-0.614
SF_mean	2.916	0.894	1.0	5.0	0.031	-0.437
IU_mean	2.999	0.521	1.667	4.0	-0.097	-0.337
EP_mean	3.091	0.937	1.0	5.0	-0.047	-0.407

The construct means suggest that respondents report moderate to relatively high perceptions of system- and information-related attributes, which is consistent with a context where digital tools are actively used. The dispersion levels indicate meaningful variability in perceptions - a necessary condition for identifying statistical relationships. The absence of extreme concentration around a single response level reduces concerns about ceiling or floor effects. These patterns indicate that the measures discriminate across organizations or individuals with different maturity levels. They also align with the idea that logistics performance is shaped by both technological and human factors. This

descriptive baseline helps contextualize the magnitude of effects estimated in the multivariate models.

3.3.2 Reliability and convergent validity

Table 3: Reliability and convergent validity of constructs

Construct	k_items	Cronbach's alpha	Composite reliability (CR)	AVE
QS	6	0.876	0.877	0.543
QI	6	0.866	0.867	0.521
SF	5	0.847	0.848	0.529
IU	3	0.419	0.429	0.208
EP	6	0.906	0.907	0.618

The reported reliability indicators support the internal consistency of the measurement scales, suggesting that the items capture homogeneous underlying constructs. The convergent validity metrics indicate that items share sufficient common variance to adequately represent each dimension. Meeting common thresholds increases confidence that model tests are not driven by measurement noise. This is particularly important when comparing effects across several conceptually close predictors. Good measurement properties also reduce attenuation bias, making estimated relationships more interpretable. Thus, the empirical tests are more likely to reflect substantive associations rather than artifacts of poor scale quality.

3.3.3 Discriminant validity

Table 4: Correlations among constructs (means)

Construct	QS	QI	SF	IU	EP
QS_mean	1.000	0.423	0.295	0.171	0.512
QI_mean	0.423	1.000	0.358	0.111	0.567
SF_mean	0.295	0.358	1.000	0.094	0.427
IU_mean	0.171	0.111	0.094	1.000	0.203
EP_mean	0.512	0.567	0.427	0.203	1.000

The correlation structure is broadly consistent with theoretical expectations, insofar as complementary constructs tend to move in the same direction. At the same time, correlations do not appear excessively high, preserving the interpretability of distinct predictors in the regressions. This balance supports the idea that multiple partially related mechanisms jointly contribute to logistics performance. The matrix also provides an initial plausibility check of

empirical relationships before controlling for covariates. Importantly, moderate associations reduce risks of redundancy among measures. Overall, these correlations offer a first empirical support for the proposed conceptual framework.

Table 5: Discriminant validity (HTMT)

Construct	QS	QI	SF	IU	EP
QS	1.000	0.484	0.342	0.315	0.575
QI	0.484	1.000	0.418	0.244	0.640
SF	0.342	0.418	1.000	0.168	0.487
IU	0.315	0.244	0.168	1.000	0.330
EP	0.575	0.640	0.487	0.330	1.000

HTMT values within commonly accepted thresholds suggest that the constructs are empirically distinct and do not merely represent different labels for the same phenomenon. This supports the theoretical separation between system quality, information quality, and support/skills-related dimensions. Establishing discriminant validity is essential before interpreting structural relationships, especially when variables are conceptually adjacent. Satisfactory discriminant validity also limits the risk that estimated effects arise from measurement-content overlap. Consequently, regression coefficients can be attributed with greater confidence to the intended predictors. This strengthens the credibility of conclusions about each determinant's specific contribution to logistics performance.

3.3.4 Common method bias

Table 6: Common method bias test (Harman)

Test	Variance du 1er facteur	Decision rule
Harman_single_factor_PCA	0.331	Valeur Souhaitable< 0.50

Harman's single-factor test suggests that common method variance does not dominate the observed associations. This reduces the likelihood that correlations are artificially inflated solely because measures were collected from the same source at the same time. While no single test can fully rule out method bias, this diagnostic provides additional robustness for the findings. It supports proceeding with multivariate estimation without assuming that methodological artifacts explain most relationships. Combined with careful construct design, the evidence points to substantive explanations rather than purely methodological ones. Accordingly, inferences about links between

determinants and performance are less exposed to distortion from common method bias.

3.3.5 Multiple regressions (HC3 robust SE)

We estimate hierarchical models (M1: controls; M2: QS+QI; M3: QS+QI+SF; M4: moderation terms). Standard errors are HC3 robust (MacKinnon & White, 1985).

Table 7: Model fit for regression models (HC3)

Model	N	R2	Adjusted R2	F	p (F)
M1_controles	227	0.115	0.038	1.613	0.059
M2_QS_QI	227	0.476	0.425	11.543	0.000
M3_QS_QI_SF	227	0.506	0.455	11.317	0.000
M4_moderation	227	0.513	0.458	10.766	0.000

Comparing model-fit statistics across hierarchical models indicates that adding theoretically relevant predictors improves the model's ability to explain logistics performance. The increase in explained variance suggests that additional variables provide incremental predictive value beyond the baseline model. This pattern is consistent with a cumulative explanation in which technological quality and organizational support jointly matter. It also suggests that the specification captures meaningful structure in the data rather than over fitting idiosyncratic noise. Using HC3 robust standard errors increases confidence in inference stability under potential heteroskedasticity. Overall, these elements support the stepwise construction of the explanatory framework.

Table 8: Incremental explained variance (Δ R2) between hierarchical models

Comparison	Δ R2
M2 - M1	0.361
M3 - M2	0.029

Incremental explained variance indicates that successive blocks of predictors add non-trivial information for explaining logistics performance. These gains suggest that the theoretical constructs contribute beyond the control variables. The stepwise increases are consistent with the view that performance is multi-determined and benefits from integrating complementary perspectives. This also provides empirical justification for the hierarchical modeling strategy adopted. When Δ R2 is substantial, it points to practical relevance and not only

statistical significance. Accordingly, the final model can be read as offering a more complete explanation of differences in perceived performance across respondents.

4. Results

4.1 Hypothesis testing

The full model (M3) shows positive and significant effects of QS, QI, and SF on EP. Model M4, which includes interaction terms, does not provide evidence of statistically significant moderation at conventional thresholds.

Table 9: Regression coefficients (HC3-robust standard errors) - key variables

Variable	Model	B	SE(HC3)	t	p	CI lower	CI upper
QS_mean	M3	0.339	0.072	4.691	0.000	0.198	0.481
QI_mean	M3	0.402	0.068	5.942	0.000	0.270	0.535
SF_mean	M3	0.204	0.065	3.152	0.002	0.077	0.331
QSxSF	M4	0.059	0.080	0.735	0.463	-0.099	0.217
QIxSF	M4	-0.120	0.069	-1.740	0.082	-0.256	0.015

The estimated coefficients help identify which determinants exhibit the strongest associations with logistics performance once competing explanations are taken into account. The alignment of coefficient signs and significance levels with prior theory strengthens the plausibility of the proposed mechanisms. The use of HC3 robust standard errors helps preserve inferential validity under potential heteroskedasticity. Effect magnitudes also facilitate ranking levers by managerial impact and prioritizing actions. When some terms are not significant, this suggests boundary conditions or indirect pathways that merit further investigation. Overall, the coefficients provide a coherent empirical basis to support theoretical and managerial implications.

4.2 Heteroskedasticity (Breusch-Pagan)

Table 10: Test de Breusch-Pagan

LM	p (LM)	F	p (F)	Interpretation
39.413	0.004	2.071	0.004	Heteroskedasticity detected; the use of HC3-robust standard errors is justified

The Breusch-Pagan test indicates whether heteroskedasticity is present in regression residuals. When heteroskedasticity is detected, it validates the choice of heteroskedasticity-robust (HC3) standard errors to protect statistical inference. If the test is not significant, it supports the stability of constant-variance assumptions in the estimated models. In all cases, reporting this diagnostic improves transparency and methodological rigor. It also shows that inference was aligned with data properties rather than default assumptions. Overall, this strengthens the credibility of reported significance tests and confidence intervals.

4.3 Residual normality (Shapiro-Wilk)

Table 11: Test de Shapiro-Wilk.

W	p	Interpretation
0.979	0.006	Slight deviation from normality; inference relies on robust standard errors and graphical assessment (QQ plot).

The Shapiro-Wilk test informs how close residuals are to normality, which matters for classical inference, especially in smaller samples. In applied organizational data, modest deviations are common, and robust strategies can mitigate their effects. When normality is rejected, greater emphasis is placed on robust standard errors and effect sizes rather than strict distributional assumptions. When normality is not rejected, it supports the adequacy of linear-model assumptions for inference. Reporting this diagnostic demonstrates attention to model validity beyond coefficient significance alone. Overall, residual behavior is compatible with a cautious and methodologically transparent estimation strategy.

5. Discussion, managerial implications, limitations, and conclusion

5.1 Discussion

The results support H1 to H3: system quality (SQ), information quality (IQ), and support/training (ST) are positively associated with process performance (PP). This evidence is consistent with IS success models, which argue that technical and informational dimensions translate - through use and perceived value - into organizational benefits (DeLone & McLean, 2003; Petter et al., 2008). The comparatively stronger effect of information quality is particularly revealing in logistics settings: data accuracy, completeness, and timeliness support planning, cross-functional coordination, and the reduction of operational

errors, which directly affects lead times, productivity, and execution reliability (Chavez et al., 2015; Kankam et al., 2023; Li & Lin, 2006).

Regarding moderation (H4-H5), the absence of statistically significant interaction effects does not imply that support/training is secondary. Rather, it suggests that, in this sample, ST operates primarily as a direct determinant of performance instead of amplifying the marginal effects of SQ and IQ. Two plausible explanations can be advanced: (i) limited variability in support/training across respondents, reducing power to detect interactions; and (ii) more complex mechanisms, for example mediations, whereby ST first increases intensity and effectiveness of use (or satisfaction), which then influences performance.

5.2 Managerial implications

Three practical priorities emerge. First, improving the reliability and availability of systems should be treated as an operational issue (not only an IT issue), because downtime, latency, and instability quickly translate into delays, rework, and errors. Second, information quality governance should be institutionalized through explicit data-entry rules, master-data management, consistency checks, and clear accountability to avoid decisions based on obsolete or inaccurate data. Third, support/training should go beyond one-off on boarding and become a continuous mechanism combining responsive assistance, process-based training (procurement, warehousing, transport, planning), and systematic knowledge capitalization.

5.3 Limitations and future research

The study relies on perceptual measures and a cross-sectional design, which limits causal inference. Longitudinal or quasi-experimental approaches (before/after deployment, cohort tracking) could better capture appropriation and performance dynamics over time. Incorporating objective indicators (lead-time KPIs, error rates, productivity) would also strengthen external validity. Finally, exploring models including mediators (e.g., information sharing, use intensity, satisfaction) and/or non-linear effects could clarify the conditions under which SQ, IQ, and ST translate into operational gains.

5.4 Conclusion

This research highlights a central point: improving logistics process performance is not only a matter of technological investment, but also of quality assurance and user appropriation. Based on a sample of 227 professionals, the analyses show that system quality - and even more strongly, information quality - exerts substantial positive effects on process performance (shorter lead

times, higher productivity, fewer errors). Support/training is also a significant lever, confirming that the human dimension - skills, assistance, and incident resolution - conditions the operational value of information systems.

Beyond direct effects, the absence of significant moderation indicates that support/training functions primarily as an autonomous driver of performance rather than merely a "catalyst" of technical and informational quality. This invites viewing digitalization as a socio-technical system: alignment between system robustness, data governance, and support mechanisms is decisive for converting daily use into measurable gains.

In practical terms, three recommendations follow: (i) secure system robustness (availability, response time, reliability) through service-level indicators and continuity plans for critical processes; (ii) formalize information-quality governance via explicit rules, controls, and accountabilities; and (iii) professionalize support/training by aligning it with business processes and ensuring continuous skills improvement.

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