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Digitalization, Operational Capabilities, Supply Chain Performance and Production Quality in Moroccan Industrial Firms: Direct and Mediated Effects.

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Abstract

Digitalization is associated with better supply chain performance and production quality in Moroccan industrial firms, but only part of that association runs through the operational capabilities that theory emphasizes. We tested a parallel mediation model with partial least squares structural equation modeling (PLS-SEM) on survey data from 217 managers and engineers, 161 of them in the automotive sector. Two specifications were compared: a baseline model in which digitalization acts only through the capabilities, and a competing model that also lets it affect both outcomes directly. The measurement model met conventional criteria (loadings 0.732 to 0.920; average variance extracted 0.645 to 0.803). Digitalization was closely tied to all three capabilities, supply chain integration, real-time data access and automated quality control ($\beta = 0.615$ to 0.698). In the competing model, which explained 61.3% of the variance in supply chain performance and 53.2% in production quality, digitalization kept significant direct effects on both outcomes ($\beta = 0.338$ and 0.239), so mediation was partial. Automated quality control was the only capability that transmitted digitalization to both outcomes (indirect effects of 0.166 and 0.264). Supply chain integration contributed weakly to supply chain performance (0.093), and real-time data access did not mediate once the direct effects were controlled. Through the three capabilities together, roughly 52% of the total effect of digitalization on supply chain performance (0.702) and 61% of its total effect on production quality (0.610) were transmitted. The results qualify the claim that digital technology acts mainly by building capabilities, and they identify automated quality control as the capability that carries most of the indirect effect.

Keywords: digitalization; supply chain integration; real-time data access; automated quality control; supply chain performance; production quality; PLS-SEM

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1. Introduction

Manufacturers have installed sensors, cloud platforms and connected planning systems faster than the evidence has accumulated on how those investments reach the income statement. Reviews of digital supply chains and Industry 4.0 describe a long list of enabling technologies and a shorter, less consistent list of measured benefits (Büyüközkan & Göçer, 2018; Ghobakhloo, 2018). Survey work on Industry 4.0 adoption points the same way: firms combine "front-end" and "base" technologies in very different patterns, and the performance they expect from them varies with the pattern (Dalenogare et al., 2018; Frank et al., 2019). Adoption, in other words, is observable; the route from adoption to results is not.

The literature leaves that route hard to read, for two reasons. The first is conceptual. Information systems research has long held that technology seldom yields an advantage by itself; value appears when it is converted into organizational capabilities that competitors cannot easily copy (Bharadwaj, 2000; Wade & Hulland, 2004). Regressing performance on a digitalization score skips precisely that conversion. The second reason is empirical. Studies that do look at mediating capabilities tend to take one capability and one kind of outcome at a time: supply chain integration and operational results (Flynn et al., 2010; Huo, 2012), data analytics and firm performance (Wamba et al., 2017; Gunasekaran et al., 2017), automated inspection and defect rates (Psarommatis et al., 2020). Whether these capabilities work side by side, and which one counts more for which outcome, is seldom tested within a single model.

The subject of this paper is the route by which digitalization reaches operational performance in Moroccan industrial firms, and its objective is to test whether, and through which capabilities, that route runs. We treat digitalization as an antecedent resource and examine three capabilities that sit at different points of the manufacturing system: supply chain integration, which governs coordination with suppliers and customers; real-time data access, which determines how quickly information about operations reaches decision makers; and automated quality control, which embeds inspection in the production process. The model gives an empirical form to the argument of our earlier conceptual work, in which digitalization acts as a meta-capability that orchestrates other operational competences (Bazouz et al., 2025). We then relate these capabilities to two outcomes that are measured at different levels, supply chain performance at the level of the network and production quality at the level of the plant. Specifically, we ask:

(1) Does digitalization strengthen each of the three capabilities?

(2) Are the capabilities associated with better supply chain performance and production quality?

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(3) To what extent do the capabilities transmit the effect of digitalization to the two outcomes, and does one of them carry a disproportionate share?

We answer these questions with partial least squares structural equation modeling (PLS-SEM) applied to survey data from 217 respondents working in industrial firms in Morocco, most of them in the automotive sector. PLS-SEM is a fitting choice here. The model is complex, several mediators are estimated at once, and the aim is to explain and predict endogenous constructs rather than to reproduce a covariance structure (Hair et al., 2019).

The paper contributes in three ways. First, it tests a parallel mediation model in which digitalization reaches performance through capabilities of different kinds, rather than folding them into a single index of "digital maturity." Second, it separates an outcome at the level of the supply network from one at the level of the plant, and shows that a capability can matter differently depending on where performance is observed. Third, it brings evidence from Moroccan manufacturing, where the automotive industry has grown into a major export activity organized around assembly plants and tiers of suppliers, and where, to our knowledge, systematic evidence on the operational payoff of digital investment is still limited. For managers the result bears on how investments are sequenced: if the capabilities are what produce the gains, spending on technology without matching spending on integration practices, data access and inspection routines is unlikely to pay for itself.

The rest of the paper is organized as follows. Section 2 sets out the theoretical background and derives fifteen hypotheses. Section 3 describes the research approach, the sample, the measures and the analytical procedure. Section 4 reports the results, Section 5 discusses them against prior work, and Section 6 closes with the conclusions, the managerial implications and the limitations of the study.

2. Theoretical background and hypotheses

2.1 Theoretical lens

Two perspectives frame the model, building on the conceptual framework we proposed earlier, which treats digitalization as an organizational meta-capability combining technological resources, adaptive processes and the use of information (Bazouz et al., 2025). The resource-based view holds that sustained advantage comes from resources that are valuable, rare and hard to imitate, and that a resource creates advantage only when the firm can deploy it through organizational routines (Barney, 1991). Dynamic capabilities research adds that firms must integrate and reconfigure their resources as conditions change (Teece et al., 1997). For information technology, the implication is that digital infrastructure serves as a foundation

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rather than as a source of advantage in itself; the advantage shows up in the capabilities built on top of it (Bharadwaj, 2000; Wade & Hulland, 2004).

The information processing perspective explains why these particular capabilities matter. Organizations facing uncertainty need an information processing capacity that matches it, which they can obtain by investing in information systems or by creating lateral relations (Galbraith, 1973). In supply chains, the fit between processing needs and capacity has been tied to how partners share information and coordinate (Premkumar et al., 2005). Supply chain integration and real-time data access are two ways of raising that capacity. Automated quality control applies the same logic inside the plant, where inspection data are produced and acted upon without manual intermediation.

We use *digitalization* to denote the extent to which a firm has embedded digital technologies in its operations and interfaces with partners, in the sense used in the digital transformation literature (Vial, 2019; Verhoef et al., 2021). The three mediators are defined as follows. *Supply chain integration* is the degree to which a firm coordinates strategically with its suppliers and customers and manages intra- and inter-organizational processes collaboratively (Frohlich & Westbrook, 2001; Flynn et al., 2010). *Real-time data access* is the extent to which relevant operational data are available to decision makers at the moment they are generated. *Automated quality control* is the extent to which inspection, measurement and defect detection are performed by automated systems within the production process. The outcomes are *supply chain performance*, understood as the effectiveness and efficiency with which the chain meets customer requirements (Beamon, 1999; Gunasekaran et al., 2004), and *production quality*, understood as the conformity of production output to specification.

2.2 Digitalization and operational capabilities

Digital tools reduce the cost of exchanging information across organizational boundaries. Shared platforms, electronic data interchange and connected planning systems lower the technical barrier to the information sharing and joint planning that define integration (Frohlich & Westbrook, 2001; Büyüközkan & Göçer, 2018). A firm that has already digitized its own processes is better placed to connect with partners, since its internal data are structured and accessible.

H1. Digitalization is positively associated with supply chain integration.

Real-time data access leans even more heavily on digital infrastructure. Sensors, machine connectivity and integrated information systems capture data where they are generated and make them available without delay (Zhong et al., 2017; Ivanov et al., 2019). From the

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information processing standpoint, this expands a firm's capacity to handle operational uncertainty (Galbraith, 1973).

H2. Digitalization is positively associated with real-time data access.

Automated quality control likewise requires digital foundations: machine vision, inline measurement and automated defect classification all presuppose digitized production equipment and data pipelines (Psarommatis et al., 2020; Zonnenshain & Kenett, 2020; Sony et al., 2020).

H3. Digitalization is positively associated with automated quality control.

2.3 Operational capabilities and performance

The relationship between supply chain integration and performance is among the most studied in operations management. Integration with suppliers and customers generally improves operational and business performance, most of all when internal and external integration are pursued together (Flynn et al., 2010; Huo, 2012). The mechanisms are easy to picture: faster responses to changes in demand, smaller inventory buffers, fewer failures of coordination. They also bear on quality, since shared specifications, early supplier involvement and joint problem solving reduce the defects that enter production from upstream.

H4. Supply chain integration is positively associated with supply chain performance.

H5. Supply chain integration is positively associated with production quality.

Real-time access to operational data helps performance because decisions rest on current rather than lagged information. With visibility into inventory, orders and process status, planners can reroute, expedite or reschedule before a disruption spreads (Christopher & Lee, 2004; Ivanov et al., 2019), and data-driven decision making has been associated with better supply chain and organizational performance (Wamba et al., 2017; Gunasekaran et al., 2017). Inside the plant, immediate access to process data permits earlier detection of drift and faster correction, which limits the volume of nonconforming output (Zhong et al., 2017).

H6. Real-time data access is positively associated with supply chain performance.

H7. Real-time data access is positively associated with production quality.

Automated quality control acts on quality most directly. Automated inspection removes much of the variability of manual checking, can examine every unit rather than a sample, and feeds defect information back to the process quickly enough to prevent repeated errors (Psarommatis et al., 2020; Zonnenshain & Kenett, 2020). Fewer defects, in turn, mean less rework and scrap, fewer returns and more reliable delivery, so quality management practices

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tend to carry through to broader firm and chain performance (Sousa & Voss, 2002; Kaynak, 2003).

H8. Automated quality control is positively associated with production quality.

H9. Automated quality control is positively associated with supply chain performance.

2.4 The mediating role of operational capabilities

If digitalization is a foundation and the capabilities are what convert it into results, the capabilities should transmit a substantial share of the effect of digitalization on performance. This is the central claim of the resource-based treatment of information technology (Bharadwaj, 2000; Wade & Hulland, 2004), and it implies a specific indirect effect for each combination of capability and outcome. The three capabilities are conceptually distinct but likely to be correlated, so we model them in parallel rather than in sequence and interpret each indirect effect as conditional on the others (Preacher & Hayes, 2008; Hayes, 2018). The theory does not rule out that digitalization also affects the outcomes through channels that the three capabilities do not capture, for example through learning effects or through better process documentation. We therefore estimate the indirect effects alongside the direct effects of digitalization on both outcomes, without positing the sign of the direct effects in advance, which allows complementary, competitive and indirect-only mediation to be told apart (Zhao et al., 2010; Nitzl et al., 2016).

H10. Supply chain integration mediates the relationship between digitalization and supply chain performance.

H11. Supply chain integration mediates the relationship between digitalization and production quality.

H12. Real-time data access mediates the relationship between digitalization and supply chain performance.

H13. Real-time data access mediates the relationship between digitalization and production quality.

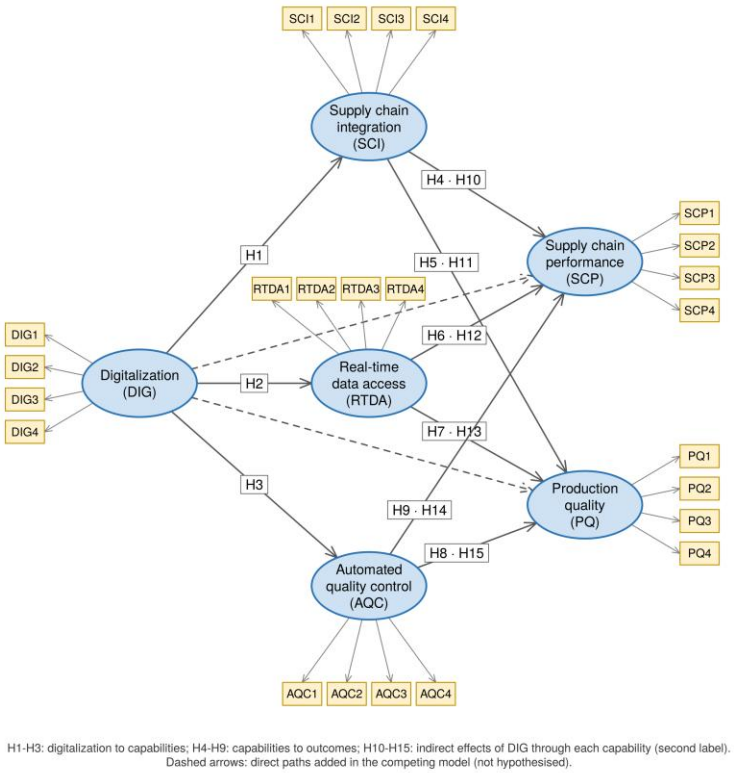
H14. Automated quality control mediates the relationship between digitalization and supply chain performance.

H15. Automated quality control mediates the relationship between digitalization and production quality.

Figure N°1 summarizes the conceptual model. Solid arrows are the hypothesized paths; dashed arrows are the direct paths added in the competing model (Section 3.4). H1 to H3 link digitalization to the capabilities; H4 to H9 link each capability to the two outcomes (H4 and H5

for supply chain integration, H6 and H7 for real-time data access, H8 and H9 for automated quality control); H10 to H15 are the corresponding indirect effects.

Figure N°1 : Conceptual model and hypotheses



H1-H3: digitalization to capabilities; H4-H9: capabilities to outcomes; H10-H15: indirect effects of DIG through each capability (second label).
Dashed arrows: direct paths added in the competing model (not hypothesised).

Source : Authors' own elaboration.

3. Methodology

The study follows a post-positivist, hypothetico-deductive approach. The hypotheses in Section 2 were derived from the resource-based, dynamic capabilities and information processing literatures before any data were collected, and they are tested against quantitative survey data. The reasoning is therefore deductive: it moves from theory to testable propositions and then to their empirical support or rejection. This position treats the constructs as measurable, if imperfectly, through respondents' reports, and treats the estimated relationships as probabilistic statements about industrial firms in Morocco rather than as general laws. It also bounds the claims that can be made. Because the data were collected at one point in time from a single respondent per questionnaire, the estimates describe associations that are consistent with the proposed causal order; they do not establish causation. A survey was preferred to case studies because the research questions concern the size and the relative weight of effects across many firms, which requires a degree of variation that a handful of cases cannot supply. PLS-

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SEM, justified in Section 3.4, fits this design because it estimates a model with several mediators jointly and evaluates its explanatory and predictive power.

3.1 Research design, sample and data collection

We used a cross-sectional online survey of managers and engineers working in industrial firms in Morocco, mostly in the automotive sector. The questionnaire was administered in English between 11 December 2025 and 25 March 2026. Respondents held operational and managerial roles that give direct knowledge of digital systems, production and logistics: methods and process engineers (14.7%), production managers (11.5%), quality and QHSE managers (11.1%), consultants (9.2%), supply chain managers (7.4%) and industrial directors (2.8%), among others. Invitations were sent by e-mail, through professional groups and directly to companies. About 850 people were approached and 252 submissions were received, a response rate of about 30%, of which 217 were complete.

The survey file contained 252 submissions. Four were empty and 31 more left at least one item unanswered; we removed these listwise, which left 217 complete responses. Of these, 161 (74.2%) came from automotive firms, 16 from aerospace, 8 from electronics and 32 from other sectors, among them food processing, textiles, energy, plastics and a few service activities. Respondents were not screened by job title or sector beyond completeness, and Section 4.6 reports a sensitivity analysis restricted to the 161 automotive respondents. The sample leans toward large firms (77.4% with more than 500 employees) and toward the Rabat-Salé-Kénitra region (59.9%), as Table N°1 shows.

Table N°1 : Sample profile (N = 217)

Characteristic	n	%
Sector		
Automotive	161	74.2
Aerospace	16	7.4
Electronics	8	3.7
Other sectors	32	14.7
Firm size (employees)		
More than 500	168	77.4
201 to 500	23	10.6
51 to 200	16	7.4
Fewer than 50	8	3.7
Missing	2	0.9
Professional experience		
More than 10 years	74	34.1
6 to 10 years	52	24.0
3 to 5 years	29	13.4
Fewer than 3 years	62	28.6
Region		

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Characteristic	n	%
Rabat-Salé-Kénitra	130	59.9
Casablanca-Settat	41	18.9
Tanger-Tétouan-Al Hoceïma	30	13.8
Fès-Meknès	9	4.1
Souss-Massa	3	1.4
Missing	4	1.8

Source : Authors' survey data.

The sample size has to be judged against the weakest effects of interest. With the inverse square root method (Kock & Hadaya, 2018), 217 observations allow a path coefficient of about 0.17 or larger to be detected at the 5% significance level with 80% power. Several paths of the competing model are smaller than that, the smallest estimates being 0.073 and 0.083, so a non-significant result for such paths is inconclusive and should not be read as evidence of no effect.

3.2 Measures

All six constructs were measured reflectively with four items each, 24 items in total, on a five-point agreement scale (1 = strongly disagree, 5 = strongly agree) with a neutral midpoint. The items were adapted from the literature on digital manufacturing, supply chain integration, real-time data use, automated quality control, and supply chain and quality performance. A first list was submitted to experienced experts, who corrected the wording and retained the items they judged valid; the retained items form the instrument used here. Appendix A gives the wording of every item. Digitalization (DIG1 to DIG4) refers to enterprise resource planning systems, Internet of Things devices on production lines, traceability across the supply chain and virtual simulation tools. The integration items (SCI1 to SCI4) ask about collaboration with suppliers through integrated digital systems, the sharing of production data on digital platforms, the connection of procurement and logistics, and the involvement of suppliers in digital planning. RTDA1 to RTDA4 concern real-time visibility of production, instant analytical dashboards, real-time detection and resolution of production problems, and the real-time integration of production data with supply chain systems. AQC1 to AQC4 cover continuous automated quality monitoring, predictive analytics for quality problems, real-time alerts for operators and vision systems that detect micro-defects. The performance items (SCP1 to SCP4) address responsiveness to demand, shorter logistics lead times, reliability and logistics efficiency, and the quality items (PQ1 to PQ4) fewer defects, continuous improvement standards, data-driven quality assurance and customer satisfaction.

Four outcome items (SCP2, SCP3, PQ1 and PQ4) attribute the improvement they describe to digital tools, digitalization or automation. Such wording ties the outcome measures to the predictor, a problem taken up in Section 6.3.

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3.3 Common method bias

A single respondent supplied both the predictors and the outcomes, so common method variance is a plausible threat (Podsakoff et al., 2003). We took precautions of two kinds. By design, respondents were told that the survey served academic purposes and that their answers would remain anonymous, and the items of each construct appeared in a separate block, with the predictor and capability blocks placed before the outcome blocks. Statistically, we computed full collinearity variance inflation factors for all constructs and used 3.3 as the threshold for pathological collinearity (Kock, 2015). The values were 2.60 for digitalization, 2.22 for supply chain integration, 3.26 for real-time data access, 3.00 for automated quality control, 3.02 for supply chain performance and 2.50 for production quality. None exceeded the threshold, although real-time data access came close. Harman's single-factor test, a weak diagnostic, gave a first unrotated factor that accounts for 53.7% of the variance of the 24 items, which is above the usual 50% benchmark. Method variance therefore cannot be ruled out, and Section 6.3 returns to it.

3.4 Analytical procedure

We estimated the models in R 4.6.1 with the seminr package, version 2.6.0 (R Core Team, 2026; Ray et al., 2026), following the workflow described by Hair et al. (2021). Three considerations favored PLS-SEM over covariance-based SEM. The study is explanatory and predictive at once, the model contains five endogenous constructs and six indirect effects that must be estimated jointly, and the main interest lies in the variance explained in the outcomes (Hair et al., 2019, 2022). All constructs were specified with Mode A outer weights, the path weighting scheme for the inner model and a convergence criterion of 10^{-7}. Significance was assessed with a bootstrap of 5,000 resamples (seed 123), percentile 95% confidence intervals and two-tailed tests. The p-values were derived from the bootstrap t-statistic with $n - 1$ degrees of freedom. Missing values were handled by listwise deletion before estimation (Section 3.1).

We followed the standard two-stage evaluation sequence. The reflective measurement model was assessed through indicator loadings (0.708 or above), internal consistency reliability (Cronbach's α, ρA and composite reliability ρC, interpreted between 0.70 and 0.95), convergent validity (average variance extracted, AVE, of at least 0.50) and discriminant validity (the Fornell-Larcker criterion and the heterotrait-monotrait ratio, HTMT, against thresholds of 0.85 and 0.90; Fornell & Larcker, 1981; Henseler et al., 2015). The confidence intervals of the HTMT came from 5,000 bootstrap resamples (percentile method, computed in R). The structural model was assessed through collinearity (inner VIF below 3, with 5 as the upper

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limit), the size, sign and significance of the path coefficients, the coefficient of determination (R^2 and adjusted R^2), effect sizes (f^2; Cohen, 1988) and out-of-sample predictive power. For the latter we ran PLSpredict with 10 folds and 10 repetitions and compared the out-of-sample errors of the PLS model with those of a linear model benchmark built on the indicators of the direct antecedents (Shmueli et al., 2019). We also report the standardized root mean square residual (SRMR) as an approximate fit index, computed from the observed and the model-implied indicator correlation matrices with the same independent implementation.

We estimated two nested structural models. The baseline model corresponds to the hypotheses as stated: digitalization affects the three capabilities, and each capability affects the outcomes, with no direct effect of digitalization on either outcome. The competing model adds the two direct paths from digitalization to supply chain performance and to production quality. Mediation was tested in the competing model, where each specific indirect effect is controlled for the direct effect (Zhao et al., 2010; Nitzl et al., 2016). Specific indirect effects are the products of the path coefficients along each route and were tested with the bootstrap distribution of the product. A significant indirect effect together with a significant direct effect of the same sign indicates complementary partial mediation; with a direct effect of the opposite sign it indicates competitive partial mediation; with a non-significant direct effect it indicates indirect-only (full) mediation; and a significant direct effect with a non-significant indirect effect indicates direct-only non-mediation. The hypotheses on the paths from the capabilities to the outcomes (H4 to H9) are evaluated in the competing model, which is the more complete specification. The baseline estimates are reported for comparison.

4. Results

4.1 Measurement model

All 24 loadings exceeded the 0.708 guideline, from 0.732 for DIG1 to 0.920 for RTDA3, and every loading was significant at $p < .001$ (Table N°2). Internal consistency was satisfactory for each construct. Cronbach's α ranged from 0.817 to 0.918, ρA from 0.829 to 0.921 and composite reliability from 0.878 to 0.942, all inside the 0.70 to 0.95 band, and the AVE values lay between 0.645 and 0.803 (Table N°3). Real-time data access ($\rho C = 0.942$) approaches the 0.95 level above which indicator redundancy becomes a concern; because the scale has only four items we kept all of them.

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Table N°2 : Indicator loadings (bootstrap results, 5,000 resamples)

Construct	Indicator	Loading	Bootstrap SD	t-value	95% CI
Digitalization	DIG1	0.732	0.052	13.97	[0.615, 0.816]
	DIG2	0.853	0.031	27.76	[0.784, 0.903]
	DIG3	0.862	0.020	43.56	[0.819, 0.897]
	DIG4	0.758	0.030	25.57	[0.696, 0.812]
Supply chain integration	SCI1	0.835	0.025	33.74	[0.783, 0.880]
	SCI2	0.839	0.027	30.55	[0.777, 0.886]
	SCI3	0.854	0.022	39.12	[0.806, 0.892]
	SCI4	0.846	0.025	33.77	[0.792, 0.890]
Real-time data access	RTDA1	0.879	0.021	40.89	[0.831, 0.915]
	RTDA2	0.868	0.026	33.95	[0.811, 0.912]
	RTDA3	0.920	0.012	79.66	[0.895, 0.941]
	RTDA4	0.915	0.018	52.25	[0.876, 0.945]
Automated quality control	AQC1	0.883	0.024	36.94	[0.829, 0.923]
	AQC2	0.889	0.019	47.45	[0.849, 0.922]
	AQC3	0.852	0.028	30.06	[0.789, 0.900]
	AQC4	0.887	0.016	54.39	[0.852, 0.916]
Supply chain performance	SCP1	0.843	0.028	29.78	[0.780, 0.891]
	SCP2	0.905	0.017	53.77	[0.869, 0.934]
	SCP3	0.913	0.014	64.21	[0.882, 0.938]
	SCP4	0.898	0.019	47.99	[0.857, 0.930]
Production quality	PQ1	0.841	0.026	32.58	[0.786, 0.886]
	PQ2	0.885	0.021	41.85	[0.838, 0.921]
	PQ3	0.862	0.023	38.03	[0.814, 0.901]
	PQ4	0.889	0.020	45.28	[0.847, 0.923]

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

Table N°3 : Reliability and convergent validity

Construct	Cronbach's α	ρA	ρC	AVE
Digitalization	0.817	0.829	0.878	0.645
Supply chain integration	0.865	0.867	0.908	0.711
Real-time data access	0.918	0.921	0.942	0.803
Automated quality control	0.901	0.901	0.931	0.771
Supply chain performance	0.913	0.913	0.939	0.793
Production quality	0.893	0.896	0.925	0.756

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

4.2 Discriminant validity

The square root of each construct's AVE exceeded its correlations with all other constructs (Table N°4). The largest correlation, between automated quality control and real-time data access (0.765), stays below the square roots of both AVEs (0.878 and 0.896). The HTMT is the more demanding criterion (Table N°5). Fourteen of the fifteen ratios were below

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0.85 with upper confidence limits below 0.90. The exception is the pair automated quality control and real-time data access (HTMT = 0.839; 95% CI [0.769, 0.899]), whose upper limit sits at the 0.90 threshold. Discriminant validity therefore holds at the level of the point estimates for every pair, but these two capabilities are empirically close, a fact that matters for the interpretation of the structural results below.

Table N°4 : Fornell-Larcker criterion (diagonal: square root of AVE; off-diagonal: construct correlations)

	DIG	SCI	RTDA	AQC	SCP	PQ
DIG	**0.803**					
SCI	0.665	**0.843**				
RTDA	0.700	0.671	**0.896**			
AQC	0.620	0.617	0.765	**0.878**		
SCP	0.702	0.633	0.687	0.679	**0.890**	
PQ	0.612	0.556	0.625	0.685	0.724	**0.870**

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

Table N°5 : Heterotrait-monotrait ratio (HTMT)

Pair	HTMT	95% CI
SCI – DIG	0.776	[0.680, 0.864]
RTDA – DIG	0.795	[0.710, 0.871]
AQC – DIG	0.697	[0.603, 0.778]
PQ – DIG	0.704	[0.603, 0.798]
SCP – DIG	0.809	[0.723, 0.886]
RTDA – SCI	0.751	[0.638, 0.848]
AQC – SCI	0.698	[0.577, 0.795]
PQ – SCI	0.631	[0.502, 0.751]
SCP – SCI	0.710	[0.601, 0.803]
AQC – RTDA	0.839	[0.769, 0.899]
PQ – RTDA	0.687	[0.576, 0.783]
SCP – RTDA	0.749	[0.657, 0.829]
PQ – AQC	0.760	[0.670, 0.839]
SCP – AQC	0.750	[0.665, 0.825]
SCP – PQ	0.801	[0.707, 0.880]

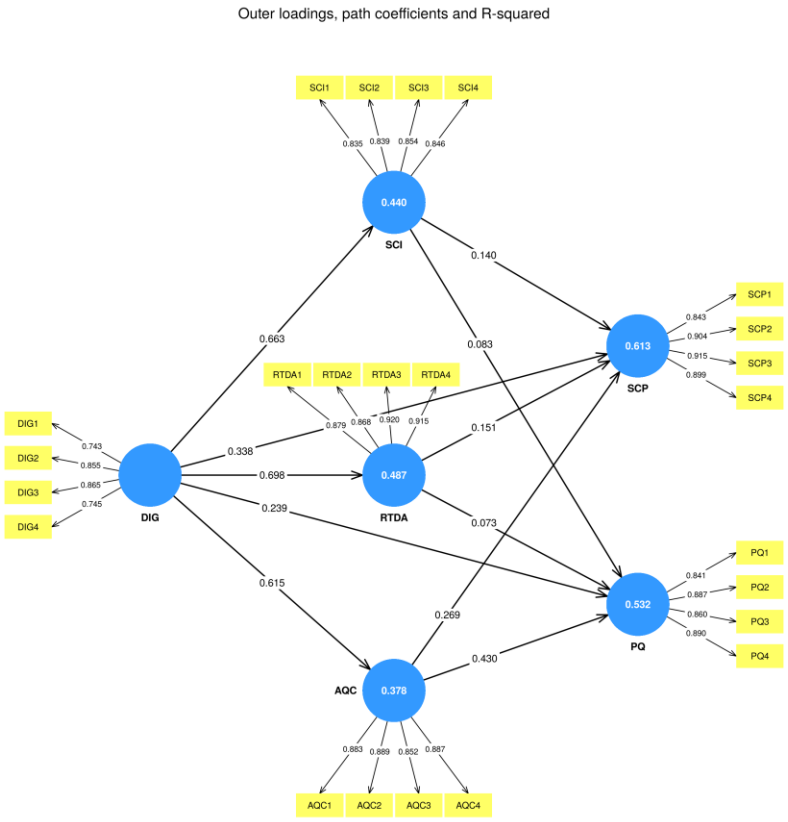
Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

4.3 Structural model and direct effects

Digitalization was strongly related to all three capabilities (Table N°6): β = 0.663 for supply chain integration, 0.698 for real-time data access and 0.615 for automated quality control, all at $p < .001$, which supports H1 to H3. The paths from the capabilities to the outcomes were smaller in the competing model than in the baseline model (Table N°7). Automated quality control was the strongest and most stable predictor, with β = 0.430 for production quality (H8) and 0.269 for supply chain performance (H9), and confidence intervals that stay well above zero. Supply chain integration had a small positive effect on supply chain performance (β =

0.140, 95% CI [0.012, 0.277], p = .039; H4), which is significant only marginally. Figure N°2 shows the estimates of the competing model.

Figure N°2 : Competing model estimated on the full sample (N = 217): outer loadings, path coefficients and R²



Source : Authors' own estimation from the survey data (R, seminr 2.6.0).

Three paths lost significance once digitalization was allowed to act directly: supply chain integration → production quality (β = 0.083, p = .300; H5), real-time data access → supply chain performance (β = 0.151, p = .098; H6) and real-time data access → production quality (β = 0.073, p = .443; H7). In the baseline model H5 and H6 had been supported (β = 0.163 and 0.283), and H7 sat on the boundary of significance (β = 0.166, p = .052). The direct effects of digitalization were significant for both outcomes: β = 0.338 for supply chain performance (p < .001) and 0.239 for production quality (p = .003). The shrinkage of the coefficients of the two correlated mediators when the direct paths enter the model suggests that the baseline estimates partly reflected the omitted direct paths.

The f^2 values for the paths from digitalization to the capabilities were large (0.607 to 0.951), but this is mechanical because digitalization is the only predictor of each capability. For the paths to the outcomes, only AQC → PQ (0.155) reached a medium effect. The direct effect

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of digitalization on supply chain performance came close to it (0.129), and the remaining values were small or negligible (0.003 to 0.073). The competing model explained 61.3% of the variance of supply chain performance (adjusted $R^2 = 0.606$) and 53.2% of production quality (0.523), against 56.3% and 50.7% in the baseline model (Table N°8). Digitalization explained the capabilities to a weak-to-moderate degree ($R^2 = 0.378$ for automated quality control, 0.440 for supply chain integration and 0.487 for real-time data access).

Table N°6 : Competing model: direct effects

Hypothesis	Path	β (SD)	t-value	p-value	95% CI	f^2
H1 (supported)	DIG → SCI	0.663 (0.042)	15.67	< .001	[0.576, 0.743]	0.784
H2 (supported)	DIG → RTDA	0.698 (0.038)	18.50	< .001	[0.624, 0.769]	0.951
H3 (supported)	DIG → AQC	0.615 (0.039)	15.79	< .001	[0.537, 0.690]	0.607
H4 (supported)	SCI → SCP	0.140 (0.068)	2.07	.039	[0.012, 0.277]	0.023
H5 (not supported)	SCI → PQ	0.083 (0.080)	1.04	.300	[−0.075, 0.241]	0.007
H6 (not supported)	RTDA → SCP	0.151 (0.091)	1.66	.098	[−0.039, 0.319]	0.018
H7 (not supported)	RTDA → PQ	0.073 (0.095)	0.77	.443	[−0.115, 0.262]	0.003
H8 (supported)	AQC → PQ	0.430 (0.081)	5.29	< .001	[0.257, 0.574]	0.155
H9 (supported)	AQC → SCP	0.269 (0.082)	3.28	.001	[0.106, 0.427]	0.073
Direct effect	DIG → SCP	0.338 (0.067)	5.03	< .001	[0.209, 0.477]	0.129
Direct effect	DIG → PQ	0.239 (0.079)	3.01	.003	[0.082, 0.396]	0.053

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

Table N°7 : Path coefficients in the baseline and competing models, β (p-value)

Path	Baseline model	Competing model
H1: DIG → SCI	0.665 (< .001)	0.663 (< .001)
H2: DIG → RTDA	0.700 (< .001)	0.698 (< .001)
H3: DIG → AQC	0.620 (< .001)	0.615 (< .001)
H4: SCI → SCP	0.254 (< .001)	0.140 (.039)
H5: SCI → PQ	0.163 (.031)	0.083 (.300)
H6: RTDA → SCP	0.283 (.002)	0.151 (.098)
H7: RTDA → PQ	0.166 (.052)	0.073 (.443)
H8: AQC → PQ	0.457 (< .001)	0.430 (< .001)
H9: AQC → SCP	0.306 (< .001)	0.269 (.001)
DIG → SCP	not in model	0.338 (< .001)
DIG → PQ	not in model	0.239 (.003)

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

Table N°8 : Explained variance

Construct	R^2 baseline	Adjusted R^2 baseline	R^2 competing	Adjusted R^2 competing
Supply chain integration	0.443	0.440	0.440	0.437
Real-time data access	0.491	0.488	0.487	0.485
Automated quality control	0.385	0.382	0.378	0.375
Supply chain performance	0.563	0.557	0.613	0.606
Production quality	0.507	0.500	0.532	0.523

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

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4.4 Mediation analysis

Three of the six specific indirect effects were significant in the competing model (Table N°9). Digitalization raised production quality through automated quality control (β = 0.264, 95% CI [0.157, 0.358]; H15) and supply chain performance through the same capability (β = 0.166, [0.064, 0.265]; H14), and it raised supply chain performance through supply chain integration (β = 0.093, [0.008, 0.189]; H10). Each of these routes coexists with a significant direct effect of the same sign, which points to complementary partial mediation. The remaining three indirect effects have confidence intervals that include zero: those through real-time data access to both outcomes (H12: 0.105; H13: 0.051) and through supply chain integration to production quality (H11: 0.055). Along these routes only the direct effect of digitalization is significant, a pattern of direct-only non-mediation, although with limited power for small effects (Section 3.1) it deserves caution.

The baseline model, which left out the direct paths, gave a different picture. Five of its six indirect effects were significant and the sixth (H13) was borderline (p = .056). The omission of the direct effects inflated the apparent mediation, and the competing model is therefore the one on which the conclusions rest. Its indirect effects add up to 0.364 for supply chain performance and 0.370 for production quality, against total effects of 0.702 (SD 0.038; 95% CI [0.623, 0.770]) and 0.610 (SD 0.043; [0.522, 0.690]). The three capabilities thus transmit about 52% and 61% of the total effects. Automated quality control alone accounts for 71% of the indirect part for production quality and 46% for supply chain performance.

Table N°9 : Specific indirect effects in the competing model

Hypothesis	Indirect path	β (SD)	t-value	p-value	95% CI	Mediation type
H10 (supported)	DIG → SCI → SCP	0.093 (0.046)	2.01	.046	[0.008, 0.189]	Complementary partial
H11 (not supported)	DIG → SCI → PQ	0.055 (0.054)	1.02	.310	[−0.048, 0.168]	Direct-only
H12 (not supported)	DIG → RTDA → SCP	0.105 (0.063)	1.67	.097	[−0.027, 0.223]	Direct-only
H13 (not supported)	DIG → RTDA → PQ	0.051 (0.067)	0.76	.445	[−0.081, 0.182]	Direct-only
H14 (supported)	DIG → AQC → SCP	0.166 (0.052)	3.21	.002	[0.064, 0.265]	Complementary partial
H15 (supported)	DIG → AQC → PQ	0.264 (0.051)	5.20	< .001	[0.157, 0.358]	Complementary partial

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

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Table N°10 : Summary of hypothesis tests

Hypothesis	Relationship	Baseline model	Competing model
H1	DIG → SCI	Supported	Supported
H2	DIG → RTDA	Supported	Supported
H3	DIG → AQC	Supported	Supported
H4	SCI → SCP	Supported	Supported (marginal)
H5	SCI → PQ	Supported	Not supported
H6	RTDA → SCP	Supported	Not supported
H7	RTDA → PQ	Not supported (p = .052)	Not supported
H8	AQC → PQ	Supported	Supported
H9	AQC → SCP	Supported	Supported
H10	Mediation by SCI, DIG → SCP	Supported	Supported (marginal)
H11	Mediation by SCI, DIG → PQ	Supported	Not supported
H12	Mediation by RTDA, DIG → SCP	Supported	Not supported
H13	Mediation by RTDA, DIG → PQ	Not supported (p = .056)	Not supported
H14	Mediation by AQC, DIG → SCP	Supported	Supported
H15	Mediation by AQC, DIG → PQ	Supported	Supported

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

4.5 Collinearity, model fit and predictive assessment

Inner VIF values in the competing model were 2.28 for digitalization, 2.16 for supply chain integration, 2.56 for automated quality control and 3.20 for real-time data access, all below the limit of 5. The value for real-time data access, slightly above 3, reflects its correlation with automated quality control (r = 0.765) and is one reason why the coefficients of the two capabilities are estimated with wide confidence intervals. The SRMR was 0.047 for the saturated model, which is below 0.08. For the estimated models it was 0.125 (baseline) and 0.110 (competing). The estimated-model values exceed the usual cutoff and fall when the direct paths are added, which agrees with the finding that the baseline structure was too restrictive.

Out-of-sample prediction was assessed with PLSpredict (Table N°11). The PLS model produced lower out-of-sample errors than the linear benchmark for 13 of the 20 indicators of the endogenous constructs in both models, which indicates medium predictive power (Shmueli et al., 2019). The advantage was clearest for supply chain performance, where all four indicators were better predicted, and weakest for automated quality control, where the benchmark based on the four digitalization items did better for three indicators than the single composite score does. Adding the direct paths lowered the out-of-sample mean squared error of supply chain performance from 0.447 to 0.407 and that of production quality from 0.500 to 0.490.

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Table N°11 : PLSpredict results (10 folds, 10 repetitions)

Construct	Out-of-sample MSE, baseline	Out-of-sample MSE, competing	Indicators with lower RMSE than the linear benchmark, baseline	Indicators with lower RMSE than the linear benchmark, competing
Supply chain integration	0.564	0.562	3 of 4	3 of 4
Real-time data access	0.518	0.519	3 of 4	3 of 4
Automated quality control	0.624	0.625	1 of 4	1 of 4
Supply chain performance	0.447	0.407	4 of 4	4 of 4
Production quality	0.500	0.490	2 of 4	2 of 4

Source : Authors' own calculations from the survey data (R, seminr 2.6.0).

4.6 Sensitivity analysis: automotive respondents only

Because 56 of the 217 respondents work outside the automotive sector, we re-estimated the competing model on the 161 automotive respondents with complete data (estimated with the independent implementation of the algorithm and the same settings). The conclusions are unchanged. The direct effects of digitalization remained significant ($\beta = 0.343$ for supply chain performance, $p < .001$; $\beta = 0.224$ for production quality, $p = .027$), automated quality control remained the strongest predictor of both outcomes ($\beta = 0.453$ and 0.272, $p \leq .005$), and the specific indirect effects were significant only through automated quality control (0.178 and 0.296) and through supply chain integration to supply chain performance (0.127, $p = .014$). Real-time data access again failed to mediate (0.095 and 0.034, $p > .20$). The explained variance was 67.4% for supply chain performance and 57.4% for production quality. Supply chain integration was a somewhat clearer predictor of supply chain performance in this subsample ($\beta = 0.203$, $p = .008$) than in the full sample.

5. Discussion

The results support the capability-based reading of digitalization only in part. Digitalization had its strongest associations with the three capabilities ($\beta = 0.615$ to 0.698), as the resource-based argument predicts (Bharadwaj, 2000; Wade & Hulland, 2004), but it also kept significant direct effects on supply chain performance ($\beta = 0.338$) and production quality ($\beta = 0.239$). The three capabilities transmitted about 52% and 61% of the total effects on the two outcomes. In other words, a substantial share of the association between digitalization and performance does not pass through the capabilities measured here. Three readings are possible, and the data cannot separate them. Digitalization may act through channels outside the model, such as process standardization, data-driven routines or workforce skills. The direct effects may also be inflated by measurement overlap, because several outcome items describe

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improvements that respondents attribute to digital tools (Section 3.2). A shared-respondent bias would push in the same direction (Section 3.3).

The comparison of the two models is, in our view, the most useful methodological result. Estimated without direct paths, which is how the hypotheses were first stated, the model supported five of the six mediation hypotheses and gave every capability a significant role in at least one outcome. Once the direct paths were added, two of those five mediation effects disappeared (H11 and H12) and the coefficients of real-time data access and supply chain integration on the outcomes shrank by roughly half. Studies that test mediation only in a model that forces full mediation, which is common in applied PLS-SEM work on digital supply chains, are therefore likely to overstate how much the capabilities explain. The direct effects of digitalization were also supported by the better out-of-sample prediction of the competing model for both outcomes.

Of the three capabilities, only automated quality control survived every specification. Its effects on production quality ($\beta = 0.430$) and on supply chain performance ($\beta = 0.269$) were significant in the baseline and competing models and in the automotive subsample, and it accounts for most of the indirect effect on production quality. The mechanism is close to the outcome: inline inspection and predictive alerts act on defects at the point where they arise, and fewer defects lower rework, returns and delivery uncertainty, which links quality practices to chain-level performance (Sousa & Voss, 2002; Kaynak, 2003; Psarommatis et al., 2020). Real-time data access, in contrast, lost its effects when the direct paths entered the model. The confidence intervals of its coefficients are wide (for example $[-0.039, 0.319]$ for supply chain performance), its correlation with automated quality control is high ($r = 0.765$; HTMT = 0.839), and its inner VIF reaches 3.20, so the data are compatible with a modest effect that the sample cannot separate from that of its neighbour. A more specific possibility is that real-time data serve production quality mainly by feeding automated inspection. Such a serial route, from digitalization to real-time data access to automated quality control to the outcomes, is consistent with the information processing logic (Galbraith, 1973) and is the natural next model to test.

Supply chain integration followed another pattern. Its effect on supply chain performance was positive but weak ($\beta = 0.140$, $p = .039$) and its effect on production quality was negligible ($\beta = 0.083$), which is smaller than the literature on integration and operational performance would lead one to expect (Flynn et al., 2010; Huo, 2012). The integration items concern digital collaboration, and the sample consists mostly of large firms in sectors where supplier requirements are standardized by customers; if so, digital integration varies less across

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respondents than the other capabilities do. This explanation is conjecture and would need data on firm position in the supply network to be tested.

For theory, the findings suggest that digitalization has both an enabling role, through capabilities, and a more direct one, and that the capabilities are not interchangeable: those that sit close to the shop floor, such as automated quality control, transmit more of the effect than those that operate at the interface with partners. This refines the resource-based claim that technology yields advantage only through capabilities (Wade & Hulland, 2004), by showing that the claim holds unevenly across capabilities and outcomes.

6. Conclusion, implications and limitations

6.1 Conclusions

This study examined whether digitalization is associated with supply chain performance and production quality, directly and through supply chain integration, real-time data access and automated quality control, using data from 217 respondents in Moroccan industrial firms. Digitalization was strongly associated with all three capabilities. In the competing model, which is the basis of our conclusions, it also had significant direct effects on both outcomes, so mediation was partial. Automated quality control was the only capability that transmitted the effect of digitalization to both outcomes, supply chain integration contributed weakly to supply chain performance, and real-time data access and supply chain integration did not affect production quality once the direct paths were controlled. Together the predictors explain 61.3% of the variance in supply chain performance and 53.2% in production quality. Leaving out the direct paths would have overstated what the capabilities contribute.

6.2 Managerial implications

These results argue against judging digital investment by the technology installed, and against expecting every capability to pay off on every outcome. For production quality, automated quality control offers the clearest return: its coefficient and its indirect effect were the largest, and both held across the models and the subsample. For plants in the Moroccan automotive supply base, where quality requirements are largely set by customers, this is plausibly where digital spending is most likely to show up in results. Firms that invest in real-time dashboards and data platforms should not expect those investments, taken alone, to improve production quality or supply chain performance; the evidence is compatible with their value lying in what they supply to automated inspection and planning systems. The significant direct effects of digitalization also show that digital infrastructure brings benefits beyond the three capabilities, so investment need not wait until all three are in place. Because the

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capabilities are strongly correlated (r between 0.62 and 0.77), a plant that has built one is likely to find the others cheaper to add.

6.3 Limitations and future research

These conclusions come with limits. The first concerns measurement: four outcome items (SCP2, SCP3, PQ1 and PQ4) name digital tools as the cause of the improvement. That builds part of the predictor into the outcome and probably inflates the paths from digitalization, and from the capabilities, to performance. Re-estimating the model with neutrally worded items, or with objective indicators such as defect rates, on-time delivery or lead times, is the most important extension. Second, the design is cross-sectional and one respondent reported every construct. Method variance cannot be excluded: the full collinearity VIFs stayed below 3.3, though that of real-time data access reached 3.26, and the first factor of Harman's test explained 53.7% of the variance. A cross-sectional design also supports associations rather than causal claims, and reverse causation is conceivable, since firms with better results may have more resources to digitalize. Third, the sample is heterogeneous and not probabilistic: respondents were recruited by e-mail, through professional groups and directly in companies. They were not screened by sector or job title, 56 of the 217 come from other sectors, and large firms and the Rabat-Salé-Kénitra region are over-represented. The automotive subsample showed the same pattern, but a study of the automotive supply base drawn from a documented sampling frame would allow firmer generalization. Listwise deletion removed 35 of the 252 submissions, and we could not test whether the discarded cases differ systematically. Fourth, power is limited for small effects (Section 3.1), so the non-significant paths of real-time data access and supply chain integration are inconclusive rather than null, and the HTMT between automated quality control and real-time data access sits close to the 0.90 limit. Fifth, the model has no control variables such as firm size, sector or respondent experience. Future work could add them, test serial mediation among the capabilities, and examine moderators such as firm size or technological intensity through multigroup or moderated mediation analysis.

APPENDICES

Appendix A. Measurement items

Respondents rated every item on a five-point agreement scale (1 = strongly disagree, 5 = strongly agree).

Construct	Item	Wording
Digitalization	DIG1	Our company uses ERP systems to manage production and logistics.
	DIG2	IoT devices are integrated across our production lines.
	DIG3	Information systems enable traceability across the automotive supply chain.
	DIG4	We use virtual simulation tools to optimize our manufacturing operations.
Supply chain integration	SCI1	We collaborate with suppliers through integrated digital systems.
	SCI2	We share production data with suppliers through integrated digital platforms.
	SCI3	Procurement and logistics functions are seamlessly connected.
	SCI4	Suppliers and partners are involved in our digital planning processes.
Real-time data access	RTDA1	We have real-time visibility over production activities.
	RTDA2	Key decisions are supported by instant access to analytics dashboards.
	RTDA3	We can track and respond to production issues as they occur.
	RTDA4	We integrate real-time production data with our supply chain systems.
Automated quality control	AQC1	Automated systems continuously monitor our production quality.
	AQC2	Predictive analytics are used to anticipate potential quality issues.
	AQC3	Real-time alerts help workers correct quality deviations during production.
	AQC4	Vision systems detect micro-defects in our production processes.
Supply chain performance	SCP1	Our supply chain responds rapidly to customer demands.
	SCP2	The use of digital tools has reduced our supply chain lead times.
	SCP3	Our supply chain is more reliable due to digital transformation.
	SCP4	Operational efficiency has improved in our logistics activities.
Production quality	PQ1	Automation technologies have contributed to a reduction in quality-related defects in our production system.
	PQ2	Our production processes are aligned with continuous quality improvement standards.
	PQ3	Our quality assurance processes are supported by real-time, data-driven systems.
	PQ4	Digital quality management initiatives have led to higher customer satisfaction with our products.

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BIBLIOGRAPHY

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bazouz, K., Elatmani, M., El Kadiri, K., & El Moudden, A. (2025). Digitalization as a meta-capability: Integrating theoretical perspectives to enhance supply chain performance and production quality. *Journal of Resources Development and Management, 96*, 39–52. https://doi.org/10.7176/JRDM/96-04

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management, 19*(3), 275–292. https://doi.org/10.1108/01443579910249714

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly, 24*(1), 169–196. https://doi.org/10.2307/3250983

Büyüközkan, G., & Göçer, F. (2018). Digital supply chain: Literature review and a proposed framework for future research. *Computers in Industry, 97*, 157–177. https://doi.org/10.1016/j.compind.2018.02.010

Christopher, M., & Lee, H. (2004). Mitigating supply chain risk through improved confidence. *International Journal of Physical Distribution & Logistics Management, 34*(5), 388–396. https://doi.org/10.1108/09600030410545436

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum.

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics, 204*, 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

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

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics, 210*, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Frohlich, M. T., & Westbrook, R. (2001). Arcs of integration: An international study of supply chain strategies. *Journal of Operations Management, 19*(2), 185–200. https://doi.org/10.1016/S0272-6963(00)00055-3

Galbraith, J. R. (1973). *Designing complex organizations*. Addison-Wesley.

Ghobakhloo, M. (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management, 29*(6), 910–936. https://doi.org/10.1108/JMTM-02-2018-0057

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics, 87*(3), 333–347. https://doi.org/10.1016/j.ijpe.2003.08.003

African Scientific Journal
ISSN : 2658-9311
Vol : 03, Num 39 Décembre 2026

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis* (2nd ed.). Guilford Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Huo, B. (2012). The impact of supply chain integration on company performance: An organizational capability perspective. *Supply Chain Management: An International Journal, 17*(6), 596–610. https://doi.org/10.1108/13598541211269210

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research, 57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Kaynak, H. (2003). The relationship between total quality management practices and their effects on firm performance. *Journal of Operations Management, 21*(4), 405–435. https://doi.org/10.1016/S0272-6963(03)00004-4

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261. https://doi.org/10.1111/isj.12131

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

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

Premkumar, G., Ramamurthy, K., & Saunders, C. S. (2005). Information processing view of organizations: An exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems, 22*(1), 257–294. https://doi.org/10.1080/07421222.2003.11045841

Psarommatis, F., May, G., Dreyfus, P.-A., & Kiritsis, D. (2020). Zero defect manufacturing: State-of-the-art review, shortcomings and future directions in research. *International Journal of Production Research, 58*(1), 1–17. https://doi.org/10.1080/00207543.2019.1605228

Ray, S., Danks, N. P., & Calero Valdez, A. (2026). *seminr: Building and estimating structural equation models* (R package version 2.6.0). https://github.com/sem-in-r/seminr

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ISSN : 2658-9311
Vol : 03, Num 39 Décembre 2026

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Sony, M., Antony, J., & Douglas, J. A. (2020). Essential ingredients for the implementation of Quality 4.0: A narrative review of literature and future directions for research. *The TQM Journal, 32*(4), 779–793. https://doi.org/10.1108/TQM-12-2019-0275

Sousa, R., & Voss, C. A. (2002). Quality management re-visited: A reflective review and agenda for future research. *Journal of Operations Management, 20*(1), 91–109. https://doi.org/10.1016/S0272-6963(01)00088-2

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

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly, 28*(1), 107–142. https://doi.org/10.2307/25148626

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

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206. https://doi.org/10.1086/651257

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of Industry 4.0: A review. *Engineering, 3*(5), 616–630. https://doi.org/10.1016/j.eng.2017.05.015

Zonnenshain, A., & Kenett, R. S. (2020). Quality 4.0: The challenging future of quality engineering. *Quality Engineering, 32*(4), 614–626. https://doi.org/10.1080/08982112.2019.1706744